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Application of Area to Point Kriging to Low Birth Weight Incidence in Ghana

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Authors' contributions

This work was carried out in collaboration among all authors. Author MOF conceived the idea, secured the data, carried out the coding, did the data analysis and drafted the manuscript. Author OAYJ assisted with the securing of the data and the study design and also did the final proofreading. Author SBT studied the literature, participated in the sequence alignment and also proofread the draft. All authors read and approved the final manuscript.

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ABSTRACT

Background: The study examines the spatial distribution of low birth weight by the ten administrative Regions in Ghana using Area to Point Kriging method. Low birth weight babies, defined by World Health Organization as babies born at term who weigh less than 2.5 kg is an important indicator of reproductive health and general health status of population. The incidence of LBW is quite high in the sub region which has a public health concern.

Methods: The study used a data set based on a Multiple Indicators Cluster Survey conducted by Ghana Statistical Service in 2011 with a sample of 10,963 women within the reproductive age. The geostatistical analysis applied in this study consists of three steps: filtering of noise in the data based on Poisson kriging, mapping of the corresponding risk at a fine scale and estimating geographical clustering of the low birth weight at the administrative units

Results: This study has demonstrated how geostatistical method can be used to model low birth weight incidence by administrative units. The Area to Point method employed has given an insight

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into a more localized potential “hot spots” for low birth weight incidence. The research showed a large range of spatial autocorrelation in the northern part than in the south in the incidence of low birth weight. The risk associated with low birth weight is centred broadly in the northern districts, districts in Central region and districts in the southern part of Ashanti region in the country which coincidentally are dominated by people of Sissala, Kassena, Mamprusi, Mole Dagbani, Wassa and Akan descends.

The least affected areas are those settlements along the Volta lake who are predominantly Ewes. This suggests that low birth weight incidence in Ghana is more of an ethnic problem with some cultural undertones and parity as a main contributing factor than any other factor.

Conclusion: The geostatistical method adopted has been able to identify a more localized potential “hot spots” for low birth weight incidence that may not be evident using other non geostatistical methods. The results further show that low birth weight incidence in Ghana is more of an ethno-cultural problem with parity as a driving factor.

Keywords: Area to point kriging; low birth weight; geostatistical; autocorrelation; incidence.

1. INTRODUCTION

The aim of this study is to examine the spatial distribution of low birth weight (LBW) by the ten administrative Regions in Ghana using Area to Point Kriging method (ATP). To the best of our knowledge, the studies conducted so far in Ghana mostly describe the mean behaviour of individual mothers. That approach is completely unable to characterize the subjects which have extreme low birth weight levels of total LBW. In fact, a model (such as the normal distribution) can fit very well the central part of the distribution but be completely inadequate to represent the tails. In terms of public health, it is most important to have a better understanding of the extent and characteristics of the individuals who are most at risk of giving birth to a LBW baby. A more preferred way to deal with this problem is to use the Area to Point Kriging (ATP) or Extreme Value Theory (EVT) [1]. The geostatistical analysis applied in this study consists of three steps: filtering of noise in the data based on Poisson kriging, mapping of the corresponding risk at a fine scale and estimating geographical clustering of the LBW at the administrative units.

This application was first employed by [2] to account for spatial heterogeneity in the population of children to estimate the semivariogram of the “risk of developing cancer” from semivariogram of observed mortality rates. [3] applied binomial cokriging to produce a map of the risk of childhood cancer in the west midlands of England. Following the successful application of this methodology, [4] employed the same methodology to map lung cancer mortality across the US. [5] examined the spatial distribution of account of sudden-infant-death syndromes for 100 countries of North California. In his approach, a two-step transformation of the data was taken into account by first removing the mean variance dependence of the data and next the heteroscedasticity.

In order to address a real data problem in mapping of disease, [6,7] proposed an approach called Poisson Kriging that filters the data before mapping. Poisson Kriging is capable to be combined with stochastic simulation to come out with multiple realizations of the spatial distribution of phenomenon or disease risk. There has been remarkable geostatistical framework given to the analysis of a real data such as medial geography [8]. This has been implemented by several authors including [9] and [8] to predict area values. This approach is referred to as “area-to-point” (ATP) or “area-to-area” (ATA) kriging according to [8]. The unique feature about ATP kriging is that it allows the mapping of variability within geographical unit (polygon) and at the same time ensuring the coherence of the prediction. For instance, disaggregated estimates of count data are non-negative and the sum is equal to the original aggregated count. [10] applied ATP and ATA for analyzing the geography of offenses and for identifying significant clusters of crimes on car-related thefts in the Baltic States. [11] applied ATP to introduce sex for cancer rates, and observed the difference between age-adjusted rates and age-sex-adjusted rates. [12] also used kriging strategy (area-to-point kriging) to solve the potential mismatch between environmental information that is both objective and subjective.

In Ghana ATP kriging has not been used extensively [13,14] until recently where [15,16] applied it to Buruli ulcer and Breast cancer incidence in Ashanti & Brong Ahafo Regions and Ashanti Region respectively.

2. METHODOLOGY

2.1 Data Source and Study Area

The 2011 Multiple Indicator Cluster Survey (MICS) data was used in this study. This is a fourth round of the survey which is conducted every five years to monitor the situation of children and women in Ghana. In this survey about 10,963 women who were within the reproductive age (15 – 49 years) were selected across the ten administrative regions of Ghana. The subjects were interviewed reference to two years preceding the survey. The selection procedure was based on a representative probability sample of households nationwide from a frame of Ghana 2010 Population and Housing Census Enumeration Areas (EA's). For comparability, the MICS used an internationally standardized sampling of two-stage stratified sample design. At the first stage, a number of EA's were selected from the regions which were considered as clusters. The households in each region were then selected using systematic sampling with probability proportional to size in the second stage. Of the 12,150 households selected for the sample, 11, 925 households were contacted and duly interviewed. In the households interviewed, 10,963 women aged 15 – 49 years were identified for interview.

Estimated Population data for 2015 based on the 2010 Population and Housing Census results by Ghana Statistical Service [17] was used in computing the raw rates of LBW (Table 3). Raw rates were calculated as the number of LBW cases in each region divided by the estimated Population in 2015. In order to better appreciate the risk of the LBW, the raw rates were rescaled by multiplying it by a factor of 100,000. This expresses the raw rates as per 100,000 people.

2.2 Geostatistical Approach

2.2.1 Area-to-point (ATP) poisson kriging

The number of LBW cases follows a Poisson process. The LBW count in the regions can be viewed as a realization of a random variable which has a Poisson distribution. This Poisson process has a parameter that is the product of the population size by the local LBW risk [18]. A particular case of Area-to-area (ATA) kriging is when the prediction support is so small that it can be assimilated to a point u_s.

Let $\mathbf{u}_\alpha$ represent the centroid coordinates for each areal supports v_α and $r(u_s)$ denote the (unknown) point value of the attribute r at location u_s within a study domain D. In a geostatistical framework, the set of all point support values $\{r(u_s), u_s \in D\}$ is regarded as a joint particular realization of random variables $\{R(u_s), u_s \in D\}$. Area-to-point spatial interpolation is to predict any point value $r(u_s)$ using K areal data
$\{r(v_i), i = 1, \ldots, K\}$: leading to the following area $-$ to $-$ point Poisson kriging estimator and kriging variance.

$$\hat{r}_{PK}(u_s) = \sum_{i=1}^{K} \lambda_i(u_s) z(v_i) \quad (1)$$

$$\hat{\sigma}^2_{PK}(u_s) = C_R(0) - \sum_{i=1}^{K} (u_s) \bar{C}_R\,(v_i, u_s) - \mu(u_s) \quad (2)$$

where the areal supports v_i are disjoint and the prediction locations are arbitrary, that is, they need not be located on a regular grid and they can lie inside or outside v_i [8]. The weights $\lambda_i(u_s)$ are computed to ensure the minimization of prediction mean square error under the condition of the un-biasness of $\hat{r}_{PK}(u_s)$, and they are the solution of equation (3).

The kriging weights and the Lagrange parameter $\mu(u_s)$ are computed by solving the following system of linear equations

$$\sum_{j=1}^{K} \lambda_j(u_s) \left[\bar{C}_R(v_i, v_j) + \delta_{ij} \frac{m^*}{n(v_i)} \right] + \mu(u_s) = \bar{C}_R(v_i, u_s),\ i = 1, \ldots, K \quad (3)$$

$$\sum_{j=1}^{K} \lambda_j(u_s) = 1$$

where $\mu(u_s)$ is the Lagrange parameter, $\delta_{ij} = 1$ if $i = j$ and 0 otherwise. m^* is the population-weighted mean, $\bar{C}_R(v_i, v_j)$ is the covariance between area v_i and v_j , and $n(v_i)$ is the population at risk in area v_i. The term $\frac{m^*}{n(v_i)}$

accounts for the variability resulting from the population size. The variance is calculated as: $\hat{\sigma}_{PK}^2(u_s) = C_R(0) - \sum_{i=1}^{K} \lambda_i(u_s)\bar{C}_R(v_i, u_s) - \mu(u_s)$

where, $C_R(0) = var(R(u_s))$ and $\bar{C}_R(v_i, u_s)$ is the covariance between v_i and location $u_s$and is inferred from the experimental semivariogram by using $\bar{r}\gamma_R(h) = C_R(0) - C_R(h)$ when the variance $var(R(u_s))$ is finite.

The ATP kriging system is similar to the ATA kriging system, which is given as;

$$\sum_{j=1}^{k} \lambda_j[\bar{C}_R(v_i, v_j) + \delta_{ij}\frac{m^*}{n(v_i)}] + \mu(v_\alpha) = \bar{C}_R(v_i, v_\alpha), \qquad i = 1, \ldots, k \tag{4}$$

except for the right-hand-side term where the area-to-area covariances $\bar{C}_R(v_i, v_\alpha)$ are replaced by area-to-point covariances $\bar{C}_R(v_i, u_s)$ that are approximated as

$$\bar{C}_R(v_i, u_s) = \frac{1}{\sum_{s'=1}^{P_i} wss'} \sum_{s'=1}^{P_i} wss' C_R(u_{s'}, u_s) \tag{5}$$

Where, P_i is the number of points used to discretize the area v_i and the weights wss' are computed as for expression;s

$$\bar{C}_R(v_i, v_j) = \frac{1}{\sum_{s=1}^{p_i}\sum_{s'=1}^{p_j} wss'} \sum_{s'=1}^{p_j} wss' C_R(u_s - u_{s'}) \tag{6}$$

where p_i and p_j are the numbers of points used to discretize the two areas v_i and v_j , respectively.

ATP kriging can be computed at each node of a grid covering the study area, resulting in a continuous (isopleth) map of LBW risk and reducing the visual bias that is typically associated with the interpretation of choropleth maps. Another interesting property of the ATP kriging estimator is its coherence. The population-weighted average of the risk values estimated at the P_α points u_s discretizing a given entity v_α yields the ATA risk estimate for this entity;

$$\bar{r}_{PK}(v_\alpha) = \frac{1}{n(v_\alpha)} \sum_{s=1}^{P_\alpha} n(u_s)\bar{r}_{PK}(u_s) \tag{7}$$

Constraint (7) is satisfied if the same *K* areal data are used for ATP kriging of the P_α risk values.

2.3 Deconvolution of the Semivariogram of the Risk

ATP kriging require knowledge of the point support covariance of the risk $CR(h)$, or equivalently the semivariogram $\gamma R(h)$. This function cannot be estimated directly from the observed rates, since only areal data is available. Thus, only the regularized semivariogram of the risk can be estimated as:

$$\bar{r}\gamma_R(h) = \frac{1}{2\sum_{\alpha,\beta}^{N(h)} \frac{n(v_\alpha)n(v_\beta)}{n(v_\alpha) + n(v_\beta)}} \sum_{\alpha,\beta}^{N(h)} \left\{ \frac{n(v_\alpha)n(v_\beta)}{n(v_\alpha) + n(v_\beta)} [z(v_\alpha) - z(v_\beta)]^2 - m^* \right\} \tag{8}$$

where, $N(h)$ is the number of pairs of administrative units or areas (v_α, v_β) whose population-weighted centroids are separated by the vector *h*. The different spatial increments $[z(v_\alpha) - z(v_\beta)]^2$ are weighted by a function of their respective population sizes, $n(v_\alpha)n(v_\beta)$ / $[n(v_\alpha) + n(v_\beta)]$, which is inversely proportional to their standard deviations, [7]. Derivation of a point-support variogram $\gamma(h)$ from the variogram $\gamma_R(h)$ fitted to areal data is called the deconvolution.

Again, derivation of a point-support semivariogram from the experimental semivariogram $\hat{\gamma}Rv(h)$ computed from areal data is called "deconvolution". An operation that has been the topic of much research; [9,8] has been adopted in this research. [18] explained how the iterative procedure could be introduced for rate data measured over irregular geographical units whereby one seeks the point-support model such that, once regularized, is the closet to the model fitted to areal data. The experimental variogram was fitted using weighted least square in Space Stats developed by Biomed ware in USA. The procedure for which the theoretical variogram was fitted into experimental variogram was based on the deconvolution as explained earlier.

2.4 Cluster Analysis

A common task in health analysis is to examine administrative units in adjacent geographical locations that are significantly similar or different. Similarity between the LBW incidence rate observed within area v_β and those recorded in the $j(v_\alpha)$ neighbouring areas v_α can be computed by the local *Moran Statistic* [19] as:

$$l(v_\alpha) = \left[\frac{z(v_\alpha) - m}{s}\right] \times \left(\sum_{j=1}^{j(v_\alpha)} \frac{1}{j(v_\alpha)} \times \left[\frac{z(v_j) - m}{s}\right]\right) \quad (9)$$

where, *m* and *s* are the mean and standard deviation of the set of *N* area incident rates respectively. This local indicator of spatial association (LISA) is simply the product of the kernel rate and the average of the neighbouring rates.

The distribution of the local *Moran statistic* under the null hypothesis of complete spatial randomness is usually obtained through a random of shuffling all the count(s) except at v_α each time calculating (9) to get the distribution of simulated LISA values.

The empirical values of (9) are compared with this distribution to compute the *P value* for the test. This randomization ignores the population size associated with each areal unit; [4].

3. RESULTS AND DISCUSSION

The Fig. 1 indicates the omnidirectional variogram of Low birth weight using the risk computed from regional-level rates, using estimator (8). The experimental variogram was fitted using a Spherical model with a range 201.71 kg (Table 1). The model was deconvoluted using the iterative procedure.

The deconvoluted variogram model was then used to compute aggregated risk values at the regional level using ATP kriging, see Fig. 1. The estimation was based on k=32 closest observations, which were selected according to the population-weighted region for Area to area kriging. All maps are smoother than the map of raw rates since noise due to small population sizes is filtered.

The LBW incidence rate at the various administrative regions (Fig. 1) shows that LBW is more endemic in the northern part of the country as well as central region than any part of the country. The ATP provides the variability within each administrative region which also shows that particular districts and communities have various rates.

The districts that show high rates of incidence include almost all districts in Central region apart from Upper Denkyira West, including other districts that share boundary with the region moving into Assin South and North districts in Ashanti region, Birim district in Eastern region, Wassa districts in Western region and then Mamprusi West and East districts in the Northern region right into Upper East and Upper West regions which broadly have high rates. However, very high rates occur among the Kassena, Builsa, Bongo and Bolgatanga in Upper East and Sissala East and West, Daffiama and Lambussie districts of the Upper West region.

There are however low incidence rates recorded broadly in Volta, Greater Accra with the exception of districts that share boundary with Central region, sections of Eastern region closed to the Volta lake including Afram Plains enclave, western part of Western region (such as Bia and Juaboso districts) and north-western part of Brong Ahafo region. Almost all the districts in Volta region have low rates especially Jasikan and Krachi districts. Greater Accra apart from districts bounded by Central region has low rates within the two Ada districts. Eastern region also recorded low rates along the Volta lake, particularly Kwahu Afram Plains North/South and Kwahu South districts.

The Local Moran statistic (Fig. 3) shows that only few settlements within the two Wassa districts of the western region is significant. These administrative units by implication have high LBW incidence within the country. The fact that almost the entire administrative regions are not significant (p-value>0.05), does not imply they are free from the incidence of LBW especially as the phenomenon is shown by the results to be more of an ethno-cultural challenge than a region or area challenge. In fact, these settlements are predominantly people of Wassa descends who were classified as Akans in the MICS report.

We further compare our results with the Poverty Map for Ghana by Ghana Statistical Service [20] (Table 2) to explore whether poverty has any impact on LBW incidence or otherwise within the various regions. According to [20] report, the incidence of poverty in Ghana shows a high concentration of poverty in the North Western part of the country. Though incidence in the districts of the South Western parts is very low, there are however few districts with relatively high incidence.

Table 1. Semivariogram parameters for LBW

Name	Model type	Sill	Nugget	Range (m)	MSS error
LBW	Spherical	42.67	0.00000004	201705.676	7.267

Table 2. Poverty head count by region (poverty line = GH₵1,314)

	Census			GLSS 6			
Region	**Poverty head count**	**Standard error**	**Absolute difference (Census & GLSS6)**	**Poverty head count**	**Standard error**	**95% confidence interval**	
						Lower limit	**upper limit**
Western	19.2	0.0040	1.7	20.9	0.0252	15.94	25.82
Central	19.6	0.0072	0.8	18.8	0.0223	14.44	23.19
Greater Accra	6.6	0.0015	1.0	5.6	0.0151	2.65	8.57
Volta	33.3	0.0028	0.5	33.8	0.0343	27.12	40.57
Eastern	22.0	0.0097	0.3	21.7	0.0242	16.91	26.4
Ashanti	13.6	0.0035	1.2	14.8	0.0169	11.43	18.07
Brong Ahafo	28.6	0.0036	0.7	27.9	0.0215	23.64	32.09
Northern	44.2	0.0062	6.2	50.4	0.0318	44.12	56.59
Upper East	45.9	0.0137	1.5	44.4	0.0388	36.8	52.01
Upper West	69.4	0.0102	1.3	70.7	0.0275	65.29	76.07

Source: Ghana Statistical Service, 2010 Population and Housing Census and GLSS6

Table 3. Projected population in Ghana by LBW incidence by region

Region	2010	2000	Growth rate	Rate/100	2015 projected	LBW incidence
Ghana	24,658,823	18,912,079	2.5	0.025	27,899,195	183 (13.7)
Western	2,376,021	1,924,577	2.0	0.020	2,623,319	8 (0.6)
Central	2,201,863	1,593,823	3.1	0.031	2,564,978	30 (2.2)
Greater Accra	4,010,054	2,905,726	3.1	0.031	4,671,362	14 (1.0)
Volta	2,118,252	1,635,421	2.5	0.025	2,396,608	8 (0.6)
Eastern	2,633,154	2,106,696	2.1	0.021	2,921,494	11 (0.8)
Ashanti	4,780,380	3,612,950	2.7	0.027	5,461,534	19 (1.4)
B/A	2,310,983	1,815,408	2.3	0.023	2,589,256	13 (1.0)
Northern	2,479,461	1,820,806	2.9	0.029	2,860,449	22 (1.6)
U/E	1,046,545	920,089	1.2	0.012	1,110,863	29 (2.2)
U/W	702,110	576,583	1.9	0.019	771,394	29 (2.2)

Source: Authors

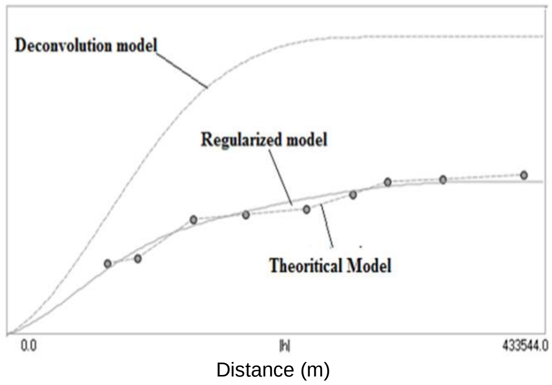

Fig. 1. Experimental variogram and model from areal data; theoretically regularized variogram and deconvoluted model for low birth weights at administrative units

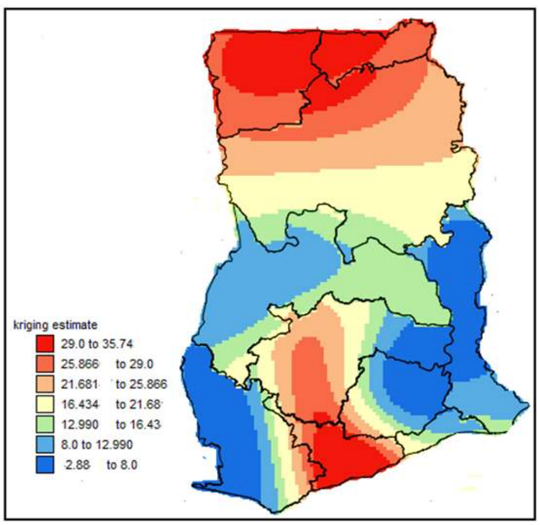

Fig. 2. ATP kriging map of LBW incidence at Regional administrative units estimated by LBW rate per 10,000 people

The concentration of poor persons is mainly observed in the northern than the southern districts of Ghana. Among the districts in Ghana, East Gonja in the Northern Region stands out as the district with most of the poor persons. Districts in the Southern Ghana on the other hand show very low concentration of poor persons, there are few districts with high number of poor persons, but these numbers cannot be compared to what pertains to districts in the northern part of Ghana.

Comparing this results [16] with our findings we can infer that to some extent there is correlation between poverty incidence and LBW incidence at least in the North Western part and mostly northern Ghana but same cannot be said in other regions especially Central and Volta regions. Central region has high LBW incidence but low poverty incidence whilst Volta has very low rate of LBW incidence but high incidence of poverty (Tables 2 and 3). The results from the spatial analysis show that incidence of LBW are high among the Akans, Mole-Dagbanis, Grussis, Assins, Wassas, Fantis, Brongs, Akims, Mamprusis, Kassins, Sissalas and the Grunis. In fact, the share of Akans and Mole-Dagbanis alone was about 72.2% of the LBW incidence and other ethnic groupings taking about 27.8%. The rate is however low among the Sefwis, Ahantas, Efutus, Aouwins and Ewes. The results show that the rates are low along the Volta River and mostly in Ewe communities in all regions. The results further show that Ewes appear to be the ethnic group likely to have low incidence of LBW in Ghana than any ethnic group. This stands to reason that the incidence of LBW in Ghana is more of an ethnic problem with cultural undertone than maternal or any other factor.

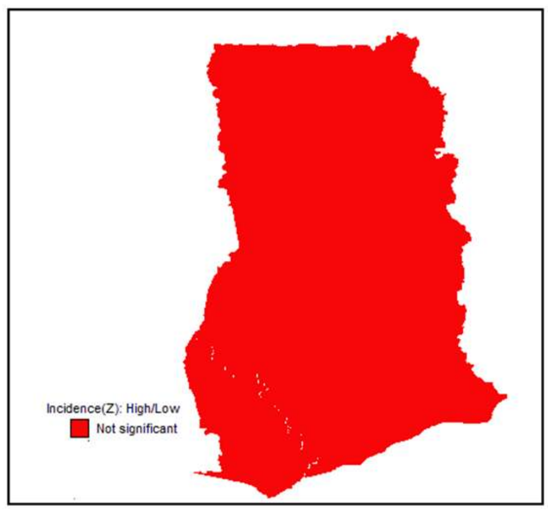

Fig. 3. Results of the local cluster analysis conducted by LBW incidence rate

4. CONCLUSION

This study has demonstrated how geostatistical method can be used to model LBW incidence by administrative units. The Area to Point kriging (ATP) method used in this study has given an insight into a more localized potential "hot spots" for LBW incidence that may not be evident when non geostatistical methods are employed. ATP kriging is used to create continuous risk surface that reduces the visual bias associated with large administrative units.

The study showed a large range of spatial autocorrelation in the northern part than in the south in the incidence of LBW. This has demonstrated that the risk associated with LBW is centred broadly in the northern districts, districts in Central region and districts in the southern part of Ashanti region in the country which coincidentally are dominated by people of Sissala, Kassena, Mamprusi, Mole Dagbani, Wassa and Akan descends.

The study further revealed that the least affected areas are those settlements along the Volta lake who are predominantly Ewes. This means that Ewe women are less likely to give birth to LBW babies than any ethnic group in Ghana. This stands to reason that LBW incidence in Ghana is more of an ethnic problem with some cultural undertones and parity as a main contributing factor than any other factor.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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