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Exploring space-time models for West Nile virus mosquito abundance data

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A B S T R A C T

This paper explores variant space-time models for log-transformed West Nile virus (WNv) mosquito data, which explicitly account for both local environmental conditions and complex dependent structures. Four space-time models take various forms to accommodate correlated structure in space and time, nested data, and nonstationarity. The average WNv mosquito abundance is captured by a global trend across all four models, but different model assumptions are imposed on the stochastic component of the proposed models: a simple multivariate linear regression model with independent and identical errors, a site-specific linear mixed model with temporally correlated errors, a week-specific linear mixed model with spatially correlated errors, and a local space-time kriging model. In a case study, the predictive performance of the four models was assessed using data collected in 2007 and 2008 for the Greater Toronto Area by the mosquito surveillance program of Ontario Ministry of Health and Long-term Care: the local space-time kriging model outperforms others, but closely followed by a site-specific linear mixed model with temporal correlation. Our findings suggest that the predictive accuracy of space-time WNv mosquito abundance models can be enhanced by explicitly taking into account spatiotemporal correlation, nonstationarity, and the data collection procedure, such as surveillance design, based on sound understanding of mosquito behavior and population dynamics.

Introduction

West Nile virus (WNv) has been recognized as a globally distributed disease since its first outbreak in New York City in 1999. Understanding the spatial and temporal patterns of mosquito population is critical for mosquito control and vector-borne disease prevention (Chuang et al., 2012; Young & Jensen, 2012). Mosquito surveillance, which typically collects mosquito counts by trap location by week, has enabled us to take timely preventive actions (CDC, 2003), although the surveillance data can not provide a measure of absolute mosquito abundance. Given that the proportion of the population counted is unknown and the effective sampling area and frequency are poorly defined (Royle, Link, & Sauer, 2002), observed mosquito count data may be loosely interpreted as indices linked to local (or relative) abundance process evolving in space and time associated with habitat attributes.

Some studies (Bandyopadhyay, Kanji, & Wang, 2012; Chuang et al., 2012; Chuang, Hildreth, Vanroekel, & Wimberly, 2011; Diuk-Wasser, Brown, Andreadis, & Fish, 2006; Hongoh, Berrang-Ford, Scott, & Lindsay, 2012; Liu & Weng, 2009; Morin & Comrie, 2010; Reisen, Fang, & Martinez, 2006; Soverow, Wellenius, Fisman, & Mittleman, 2009) have characterized the associations of meteorological and environmental conditions with mosquito abundance despite limited data availability. Both Shaman and Day (2007) and Ruiz et al. (2010) have demonstrated that increased temperature has a direct effect on the spread of WNv mosquito infection. Similarly, Diuk-Wasser et al. (2006) have identified key environmental predictors of mosquito abundance using remote sensing data and Geographical Information System (GIS) analysis. However, meteorological data collected from weather stations on a sparse network do not always allow modeling spatial variability of meteorological conditions, which are important drivers of dynamic mosquito population changes (Chuang et al., 2011). Similarly, modeling the effects of local landscape factors on the dynamic changes of mosquito population is not straightforward (Brown, Childs, Diuk-Wasser, & Fish, 2008; DeGroote, Sugumaran, Brend, Tucker, & Bartholomay, 2008; Diuk-Wasser et al., 2006; Gu, Lampman, Krasavin, Berry, & Novak, 2006): changes in the environmental conditions over time is often ignored; each species prefers a certain habitat and accordingly thrives in different landscapes with features essential to its life history (Machado–Machado, 2012); and the spatial units over which environmental

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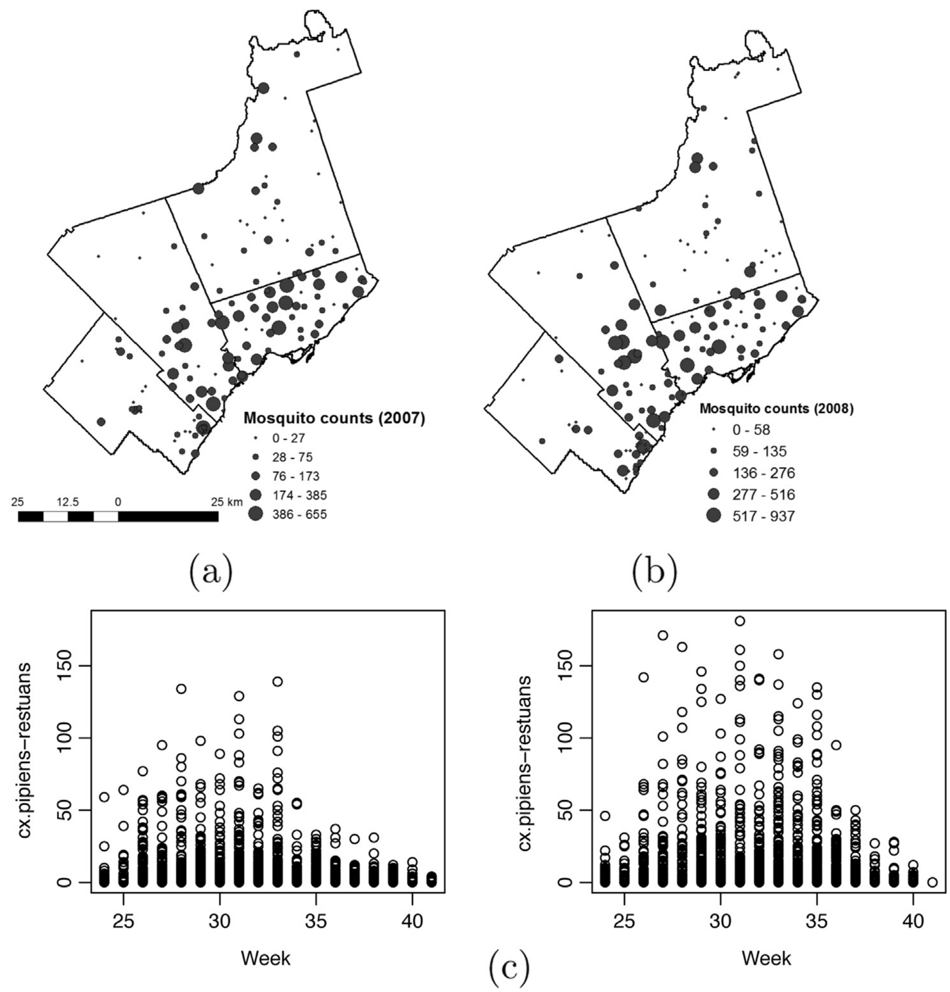

Fig. 1. Spatial distribution of mosquito counts per region (health units) in (a) 2007 and (b) 2008. The diameters of circles are proportional to the number of adult female mosquito captured at each trap site. (c) Weekly variation of mosquito counts in 2007 (left) and 2008 (right).

factors are measured are rather arbitrarily determined in terms of the size, shape, and orientation. As a result, substantial variability of mosquito abundance may not be captured when standard regression procedures with static covariates are used to predict the relative abundance from mosquito surveillance data.

In mosquito population dynamic modeling, therefore, correlated errors, nested data structure, and/or nonstationary covariance should be considered as a norm rather than a nuisance. Under the stationarity assumption, mosquito abundance inferred from a pair of trap sites is expected to be similar each other as long as the two trap sites share the same distance apart. When the stationarity assumption does not hold, that is, nonstationarity is present, the similarity or dependence between two trap sites varies with their location as well as the distance apart. Both correlated errors and nonstationarity might occur due to missing covariates or misspecification of regression models, which are commonly encountered in ecological studies (Cook & Pocock, 1983; Zuur, Leno, Walker, Saveliev, & Smith, 2009). Moreover, the scale discrepancy (Hsueh, Lee, & Beltz, 2012) in space and time between observed mosquito surveillance data and the process underlying observations may yield the correlated error structures and possibly the nonstationarity (Chuang et al., 2011; Eisen & Eisen, 2007; Moellering & Tobler, 1972; Ruiz et al., 2010; Spielman & Yoo, 2009; Walsh, Glass, Lesser, & Curriero, 2008). Lastly, the surveillance design—repeated observations obtained at each trap site and multiple observations per week—will yield nested data, which are inherently correlated in space or time (Goldstein, 1987; Pinheiro & Bates, 2000; Vanwambeke et al., 2006).

A possible solution to the problems outlined above is to develop a spatially and temporally dynamic WNv mosquito abundance model. Mixed models (also called "random effects model", "multilevel model", or "hierarchical model") can accommodate the nested structure of the surveillance data and a correlated structure of errors in space or time (Haining, 2003; Yoo, 2013; Zuur et al., 2009), but not the space-time interaction (or joint space-time correlation). On the other hand, a local space-time kriging model (Haas, 1995) can incorporate both the spatial dependence and temporal correlation of the dynamic process underlying observed mosquito data, and accommodate the nonstationarity in latent mosquito abundance process via a moving window approach. The primary goals of this article are to explore various space-time models for WNv mosquito data and to identify key factors for consideration in WNv mosquito population dynamics modeling.

Material and methods

Mosquito data

Mosquito data are obtained from the mosquito surveillance program of Ontario Ministry of Health and Long-term Care. The