# A comparison of least squares regression and geographically weighted regression modeling of West Nile virus risk based on environmental parameters

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**Background.** The primary aim of the study reported here was to determine the effectiveness of utilizing local spatial variations in environmental data to uncover the statistical relationships between West Nile Virus (WNV) risk and environmental factors. Because least squares regression methods do not account for spatial autocorrelation and non-stationarity of the type of spatial data analyzed for studies that explore the relationship between WNV and environmental determinants, we hypothesized that a geographically weighted regression model would help us better understand how environmental factors are related to WNV risk patterns without the confounding effects of spatial non-stationarity.

**Methods.** We examined commonly mapped environmental factors using both ordinary least squares regression (LSR) and geographically weighted regression (GWR). Both types of models were applied to examine the relationship between WNV-infected dead bird counts and various environmental factors for those locations. The goal was to determine which approach yielded a better predictive model.

**Results.** LSR efforts lead to identifying three environmental variables that were statistically significantly related to WNV infected dead birds (adjusted $R^2$=0.61): stream density, road density, and land surface temperature. GWR efforts increased the explanatory value of these three environmental variables with better spatial precision (adjusted $R^2$ = 0.71).

**Conclusions.** The spatial granularity resulting from the geographically weighted approach provides a better understanding of how environmental spatial heterogeneity is related to WNV risk as implied by WNV infected dead birds, which should allow improved planning of public health management strategies.

1 **A comparison of least squares regression and geographically weighted**

2 **regression modeling of West Nile virus risk based on environmental**

3 **parameters**

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17  **Abstract**

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32  significantly related to WNV infected dead birds (adjusted $R^2=0.61$): stream density, road

33  density, and land surface temperature.  GWR efforts increased the explanatory value of these

34  three environmental variables with better spatial precision (adjusted $R^2 = 0.71$).

35  **Conclusions.**  The spatial granularity resulting from the geographically weighted approach

36  provides a better understanding of how environmental spatial heterogeneity is related to WNV

37  risk as implied by WNV infected dead birds, which should allow improved planning of public

38  health management strategies.

39

## Introduction

41        West Nile Virus (WNV) is a vector-borne disease that was first detected in the United

42   States in 1999 (Nash et al. 2001). Within a few years the virus had spread across the North

43   American continent (Hayes et al. 2005). WNV has had important environmental and human

44   impacts, including a decline in numerous bird species (CDC) and increased morbidity and

45   mortality among humans. This has also resulted in increased economic burdens due to initial

46   acute health care needs of infected individuals and subsequent long-term costs associates with

47   infection, estimated at approximately $56 million per year between 1999 and 2012 (Barrett

48   2014). Because that study indicated how difficult predicting and planning for WNV outbreaks

49   was, we became interested in developing a spatially explicit model using environmental factors

50   in an attempt to improve WNV risk predictions.

51        There are two important considerations that should typically be examined when

52   developing spatially explicit environmental disease risk  models (Miller 2012). The first should

53   be an examination of potential spatial autocorrelation (the degree to which a set of spatial

54   features and their associated data values tend to be clustered together in space). This involves

55   accounting for whether environmental factors and the corresponding disease rates in

56   geographically proximate areas are more or less clustered together than they are in

57   geographically distant areas. Second, data non-stationarity (changing means, variances and

58   covariances in data across space) should be investigated and controlled when necessary

59   (Fotheringham 2009a; Miller 2012). Geographically weighted regression (GWR) can be used for

60   these two considerations and can often produce improved models that enable better spatial

61   inference and prediction. Recent studies have applied GWR modeling to drug-resistant

62    tuberculosis versus risk factors (Liu et al. 2011); environmental factors versus typhoid fever

63    (Dewan et al. 2013); local climate and population distribution versus hand, foot, and mouth

64    disease (Hu et al. 2012); and environmental factors and tick-borne disease (Atkinson et al. 2012;

65    Atkinson et al. 2014; Wimberly et al. 2008a; Wimberly et al. 2008b), all showing that predictor

66    variables varied spatially across large geographic regions, implying that the results for such

67    studies may be improved using GWR.

68         The spatially explicit model that is discussed in this paper uses GWR to account for

69    spatial heterogeneity for two reasons: (a) WNV disease risk observed across space may be

70    related to similar environmental variables that increase vector habitat suitability and (b)

71    environmental variables that influence WNV risk are not typically uniformly distributed across

72    geographic space. Although many epidemiological models of WNV risk have been developed, it

73    appears that there has been little research to explicitly examine techniques that account for

74    spatial heterogeneity. Most models assume that the impact of various environmental factors are

75    constant across the study region, which is unrealistic as larger areas display substantial variations

76    in distribution of environmental, socio-economic, and demographic conditions (Goovaerts 2008).

77         Due to the unavailability of reliable and complete data, developing models of WNV risk

78    pose additional challenges. Human case data is lacking due to issues of under-reporting and

79    limited surveillance. Our alternative strategy was to assess WNV infected dead bird counts as a

80    surrogate measure of human risk because "infection rates" in dead birds can be more precise

81    because of the genetic markers tested in dead birds may be more reliable than case data and/or

82    surveillance data.  Additionally, others have also used mosquito habitat suitability as a surrogate

83    for estimating WNV risk for human infection (Cooke et al. 2006). For our study, we followed a

84    similar approach and used a model of mosquito habitat suitability condition as a predictor of the

85   spatial distributions of infected birds, which in turn can be used to estimate WNV disease risk

86   among human populations. Further, because the environmental variables considered in this study

87   are known to vary across space, we account for spatial autocorrelation and non-stationarity using

88   GWR following the approach of (DeGroote et al. 2008) in order to improve the predictability of

89   a model.

90

91   WNV transmission and risk factors

92        The WNV transmission cycle was an important component of our modeling efforts. The

93   first step in the WNV transmission cycle primarily occurs when a competent female mosquito

94   vector bites an infected bird reservoir host, which in turn results in the virus being transmitted to

95   the mosquito (Blair 2009). This occurs when the female mosquito is seeking a blood meal to

96   obtain nutrients necessary for egg development. After taking an infectious blood meal, a

97   mosquito may pick up a permanent infection. The infected mosquito now has the potential to

98   transmit the virus to another bird or animal when it feeds again. Once infected, birds may fly to

99   other locations where the virus can be transmitted to susceptible mosquitoes. Subsequently, the

100  disease may be transmitted by infected mosquitoes to humans or other mammals that act as

101  incidental hosts. Dead birds found to be infected with WNV are often the primary indicators for

102  presence of the disease in a geographic region and have proven to be useful for disease

103  prediction modeling and identifying areas for human infection risk (Cooke et al. 2006; Ruiz et al.

104  2004; Valiakos et al. 2014). This relationship allows an assumption of a positive correlation

105  between infected dead birds and WNV risk. Since the New York outbreak in 1999, WNV has

106  been recovered from 26 mosquito species in North America, including *Culex. pipiens, Culex.*

107  *salinarius, Culex. restuans, Ochlerotatus canadensis, Oc. japonicus, Aedes vexans*, and *Culiseta*

108 *melanura* (CDC 2000; Control & Prevention 2001). Results from a study (Goddard et al. 2002)

109 assesses the vector competence of California mosquitoes. The results indicate that mosquitoes in

110 the genus *Culex* (*Cx.*)are the principal hosts of WNV in California. The study also analyzed that

111 on the basis of vector competence and host-feeding patterns, *Cx. tarsalis* may be the principal

112 vector in rural agricultural ecosystems; and *Cx. pipiens* complex and *Cx. stigmatosoma* as

113 important vectors in urban settings.

114      Vector and pathogen reservoirs overlap when certain environmental conditions are

115 present (Rochlin et al. 2011). Table 1 provides an overview of the environmental conditions that

116 are associated with WNV transmission, which were utilized for our research. These include

117 characteristics of a place such as the mosquito species habitat: climatic conditions, topography

118 and land use/land cover classes such as vegetation, water, and urbanized areas. Spectral indices

119 acquired from satellite imagery provide information about environmental characteristics like

120 temperature, vegetation cover, and moisture (Rodgers & Mather 2006). Liu and Weng (Liu &

121 Weng 2012) in a study on WNV risk in southern California found that one of the main factors

122 contributing to the WNV propagation included land surface temperature. They related higher

123 temperature to viral replication in mosquitoes for WNV to be disseminated throughout the year.

124 The results also show that areas with lower elevations tended to be more susceptible to WNV

125 invasion as mosquito population propagates in the plain habitats with warmer temperatures

126 compared to areas with higher elevation that have lower temperatures.

127      **Table 1 approximately here**

128 Statistical Considerations

129      Miller (2012) suggests that a 'global' model is the one that assumes that the parameters

130 (commonly mean and variance) of some process are constant across geographic space

131    (commonly mean and variance), typically referred to as the spatial stationarity of a process.

132    Miller suggests that in the case these parameters vary across geographic space (spatial

133    heterogeneity), then such models may lead to inaccurate predictions and subsequent problems for

134    decision-making. In an ecological context, spatial heterogeneity usually results from the

135    interaction of various environmental processes that operate at different scales (Legendre 1993).

136    Fotheringham (Fotheringham 2009b) used local statistics for linking the concepts of spatial

137    autocorrelation and heterogeneity that are deemed important when developing spatial models.

138    Local statistics disaggregate a global mean value into locally computed values for each spatial

139    unit. It is based on a conceptualization of Tobler's first law in Geography (Tobler 1970) that

140    specifies that "everything is related to everything else, but near things are more related than

141    distant things." Spatial autocorrelation is a commonly used measure of the degree of spatial

142    heterogeneity.

143        GWR is a local regression method that can be used for diagnosing spatial heterogeneity

144    between dependent and explanatory variables over space (Fotheringham et al. 2003). It is

145    performed within local windows centered on the nodes of a regular grid. Each observation within

146    the local window is weighted based on its proximity to the center of that window. This approach

147    has several advantages: it avoids abrupt changes in the local statistics computed for adjacent

148    windows, helps visualize spatial variability within the geographic entity, and allows analysis of

149    regionally aggregated data (Goovaerts 2008). A model's predictive ability, particularly in

150    ecological modeling, is influenced not only by the strength of relationships between the species

151    and its environment, but whether the model recognizes if the relationships are operating at

152    multiple spatial scales. GWR provides a framework for exploring scale-dependent effects. It tests

153    the effect on a model's predictive ability by systematically increasing the size of the local

154    window (Miller 2012).

155         GWR can be used for mapping the spatial distribution of a model's coefficient values in

156    order to identify potential missing variables or to suggest other underlying factors associated

157    with the observed non-stationarity (Miller 2012). GWR is also useful for exploratory data

158    analysis and visualization; for example Kupfer and Farris (Kupfer & Farris 2007) used a 'leave-

159    one-out' (jackknifing) methodology to compare residuals from GWR and  ordinary least squares

160    regression. They found that GWR often had more accurate predictions for sites that were

161    difficult to predict (where both models had overall higher residuals), which is why we used a

162    GWR framework for explicitly modeling the spatial relationships between WNV and its

163    environmental risk factors.

164

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166

167    **Materials & Methods**

168    Study area

169         The model was built for the state of California, which was the national epicenter of WNV

170    activity in 2004 and 2005 (Jean et al. 2007). WNV was first detected there in July 2003 (Reisen

171    et al. 2004). It is the third largest state by area in the United States and is made up of 58 counties.

172    California has the largest population in the U.S., but it is unevenly distributed across the state.

173    The state also has a variable landscape with a large valley in the middle, bounded by mountain

174    ranges.

175

176     Environmental factors and data sources

177        Our model utilized various environmental factors (Table 1) that have been suggested as

178     descriptive in local WNV risk distribution: surface slope, density of roads, density of streams,

179     monthly mean temperature, monthly mean evapotranspiration, and land cover classes like

180     vegetation, developed land, cultivated land, and open surface water. All environmental

181     parameters except roads and streams (Table 2) were acquired in grid format and resampled to

182     120 meter resolution as suggested by Cooke et al. (2006). Data resampling was done using the

183     resampling tool available in ArcGIS software. The modeling method utilized in this study was

184     based on analyzing data in raster format, and therefore road and stream vector data were

185     converted to raster format using the 'Kernel Density Estimation' tool in ArcGIS to create road

186     density and stream density grid files. The tool assumes a Gaussian distribution and thus assigns

187     more importance towards the center of kernel in comparison to the features that are further apart.

188        Various dynamic environmental data including Normalized Difference Vegetation Index

189     (NDVI), Land Surface Temperature (LST), and Evapotranspiration (ET) were downloaded from

190     the Moderate Resolution Imaging Spectroradiometer (MODIS) toolbox incorporated in

191     ArcGIS®. The Land Surface Temperature tool accesses MOD11-A1, the daily averaged LST

192     product. The MOD11 product uses the algorithm which is optimally used to separate ranges of

193     atmospheric column water vapor and lower boundary air surface temperatures into tractable sub-

194     ranges. The NDVI is calculated according to the formula NDVI = (NIR - VIS)/ (NIR + VIS)

195     where NIR is the near-infrared radiance and VIS is observed radiation in the visible spectrum.

196     NDVI data is available from either satellite with MODIS (Aqua or Terra) as a monthly average.

197     The time lag between the hatching of a mosquito egg to an adult mosquito taking blood meals

198     and becoming infected with WNV to the subsequent infection of a human and the appearance of

199    WNV disease symptoms was taken into account and therefore environmental data used for this

200    study was taken for the month of July, the month prior to peak WNV human incidence cases

201    (Campbell et al. 2002).

202        **Table 2 approximately here**

203

204    Least Squares Regression (LSR) modeling

205        WNV disease annual incidence rate (cases per 100,000 populations) was used as the

206    measure of disease severity in this study. Annual WNV-infected dead birds sentinel data,

207    averaged for 2004-2010, was used as a surrogate of WNV risk and was the dependent variable

208    for modeling purposes in this study because several other studies (Chaintoutis et al. 2014; Eidson

209    et al. 2001a; Eidson et al. 2001b; Eidson et al. 2001c; Guptill et al. 2003; Johnson et al. 2006;

210    Mostashari et al. 2003; Nielsen & Reisen 2007; Patnaik et al. 2007; Ruiz et al. 2004) have

211    suggested links between infected dead birds and WNV human infection rates. Since wild birds

212    are the primary reservoir hosts for WNV and indicator of human infection risk, we utilized this

213    association to develop the disease prediction model. We determined the utility of this

214    relationship by correlating the dead birds data with the human incidence rate ($r^2 = 0.409$,

215    determined by utilizing Ordinary Least Squares modeling within the Modeling Spatial

216    Relationships tools within the Spatial Statistics Tools toolbox incorporated in ArcGIS® Arc

217    Toolbox). While infected dead bird counts only explain about 40% of reported human cases in

218    California, it is a highly significant predictor (p=0.01). Hence we used a dead bird model, with

219    infected dead birds as a dependent variable, to assess WNV risk among human population.

220        Interpretations of ordinary Least Squares Regression (LSR) model performance were

221    based on assessing multi-collinearity, robust probability, adjusted $R^2$, and Akaike's information

222    criterion (AIC) (Akaike 1974). Multi-collinearity was assessed through the variance inflation

223   factor (VIF) statistic, which measures redundancy among explanatory variables. Explanatory

224   variables associated with VIF values larger than about 7.5 indicate that these variables are

225   providing similar information, and they were removed one at a time from the model based on

226   VIF value until the model became unbiased.  Robust probability indicates the statistically

227   significant variables that are important to the regression model. Examining VIF values and

228   robust probability, we ran and re-ran LSR models until narrowing down to non-redundant and

229   significant variables: land surface temperature; stream density, and; road density. Akaike's

230   information criterion (AIC) was then used to determine the best LSR model.

231        The next step was to explore GWR models that might better explain the variation in

232   infected dead bird counts based upon environmental data. Spatial autocorrelation (Global

233   Moran's I) was utilized to assess whether the environmental factors exhibited a random spatial

234   pattern (Goodchild 1986), and where adequate models have a random distribution of the

235   residuals (Mitchell 2005).

236

237   Geographically Weighted Regression (GWR) modeling

238        Under conditions of non-stationarity in LSR modeling, geographically weighted

239   regression (GWR) was explored to potentially improve modeling results. These results were

240   determined by utilizing Geographically Weighted Regression modeling within the Modeling

241   Spatial Relationships tools within the Spatial Statistics Tools toolbox incorporated in ArcGIS®

242   Arc Toolbox. The same explanatory variables that were used in LSR modeling were used to run

243   GWR rather than starting with the full global set of parameters so as to avoid introducing

244   "improvement" that could not be attributed solely to which modeling approach was applied. In

245   other words, if GWR modeling was not applied to the same variables as LSR modeling, but

246    yielded better results, we would not know if the improvement was due to the modeling approach

247    or the environmental data that was used to build each model.

248        Once key environmental factors were identified during LSR modeling, we proceeded to

249    explore the spatial variability of local regression coefficients to determine whether the

250    underlying process exhibited spatial heterogeneity (Fotheringham et al. 2003). A GWR local

251    model was applied to analyze how the relationship between infected dead bird counts and

252    environmental factors changed from one county to another. Unlike conventional LSR regression

253    modeling, which produces a single regression equation to summarize global relationships among

254    the independent and dependent variables, GWR detects spatial variation within relationships in a

255    model and produces information useful for exploring and interpreting spatial non-stationarity

256    (Fotheringham et al. 2003).

257        A spatial kernel was used to provide geographic weighting for the local window centered

258    on the grid nodes used in our model. There are two possible categories of spatial kernels:

259    fixed/adaptive and bandwidth, which is a key coefficient that controls the size of the kernel

260    (Akaike 1974). These kernels tend to be Gaussian or Gaussian-like which implies that distant

261    samples are weighed lesser than the proximal ones. There are three potential bandwidth

262    approaches: Akaike information criterion (AIC), cross validation (CV), and bandwidth

263    parameter. For our GWR model, the AIC approach was chosen because the distribution of

264    infected dead birds was not consistent in the study area. The following settings were used in

265    ArcGIS GWR: Bandwidth method = AIC and Kernel type = Adaptive.

266        Finally, we examined independency and normality of residuals, to evaluate the fit of the

267    model. Local collinearity, the square root of the largest eigenvalue divided by the smallest

268    eigenvalue, of our GWR model was also assessed but no data points were removed as they

269    compromised model diagnostics.  The adjusted coefficient of determination (Adjusted $R^2$) was

270    used for comparing LSR and GWR models to determine which approach would provide a better

271    understanding of the relationship between environmental conditions and West Nile Virus risk

272    (Fotheringham et al. 2003).

273

274    **Results**

275         LSR modeling identified land surface temperature (VIF = 1.046), stream density (VIF =

276    1.177), and road density (VIF = 1.143) as statistically significant (p <0 .05) variables related to

277    WNV risk:

278

279    WNV risk = -75.87 + 595.60 (*RD*) + 1.89 (*LST*) - 146.89 (*SD*)                                    (1)

280

281    Where:

282    WNV risk = average infected dead bird count

283    *RD* = road density

284    *LST* = land surface temperature

285    *SD* = stream density

286         The histogram of the LSR model's residuals approximates that of a normal curve, with a

287    non-significant (0.134, p<0.05) Jarque-Bera statistic (Jarque & Bera 1980), and the Moran's I

288    Index Z-score (1.23) all imply that the model is unbiased and significantly different than random.

289            However, the Koenker statistic (0.000007*, p<0.05) confirmed non-stationarity in

290    the LSR model indicating that there is not a consistent relationship between the explanatory

291    variables and WNV risk across the study area. Further, the presence of mild heteroskedasticity

292     was noted in the LSR model. We conclude that the LSR model is stable but non-stationary,

293     suggesting that proceeding with GWR model was warranted.

294          The GWR model in this study was implemented using the following algorithm:

295

296     WNV risk$_{(i)}$ = $\beta_{i0}$ + $\beta_{(i1)}$ $RD_{(i)}$ + $\beta_{(i2)}$ $LST_{(i)}$ − $\beta_{(i3)}$ $SD_{(i)}$ + $\varepsilon_{(i)}$                           (2)

297     Where $\beta$ coefficients are county (i) specific, and RD is road density, LST is land surface

298     temperature, and SD is stream density.

299

300          Comparing the fit of the global LSR model (assumes homogeneity of variables across

301     space) and local GWR model (makes no assumption of homogeneity), we found that the global

302     LSR adjusted $R^2$ was 0.61 ($R^2$ was 0.66, P<0.05, Fig. 1) with analysis run on all 58 counties. The

303     local GWR adjusted $R^2$ was 0.71 ($R^2$ is 0.75, p<0.05, Fig. 2) with a bandwidth of 54, which

304     suggests that there has been some improvement by using a local modeling approach. Our

305     preferred measure of model fit, AIC, gave a value of 567.7 for the global model and 551.4 for the

306     local model. The difference of 16.3 is relatively strong evidence of an improvement in the model

307     fit to the data. Further, the problem of hetroskedasticity that was noted in the OLS model was not

308     observed in the GWR model.

309          We also tested the results using different bandwidth parameter. Several iterations were

310     run but it was observed that although a smaller band-width criterion gave an improved

311     combination of AICc and adjusted $R^2$ values, it also compromised the model diagnostics by

312     introducing local collinearity and thus instability in the model. Addressing local collinearity by

313     removing the Counties having condition number greater than 30 affected the model's overall

314   results. Thus, it is better to have a larger band-width rather than violating model assumptions and

315   to avoid the unstable prediction (Charlton & Fotheringham ; Nakaya 2014).

316
317        **Figure 1 approximately here**

318        **Figure 2 approximately here**

319

320        Mapping the values of the standardized residual across California (Fig. 3a) provides a

321   representation of: (a) areas with unusually high or low residuals and (b) whether the residuals

322   were spatially autocorrelated. Counties with excessively large positive residuals would under-

323   predict WNV risk, and counties with excessively large negative residuals would over-predict

324   WNV risk. The spatial autocorrelation of GWR residuals for our model resulted in a Moran's I

325   value of -0.11 (p=0.18), implying little evidence of any autocorrelation in them.

326        **Figure 3 approximately here**

327        Local coefficient estimates for significant factors were mapped using quantile

328   classification method. Figure 3b shows the variation in the model's coefficient estimates for the

329   land surface temperature (LST) variable. The map for the local coefficients reveals that the

330   influence of this variable in the model varies considerably over California, with a strong north-

331   south direction. The range of the local coefficient is from 1.26 for the northernmost counties to

332   3.06 for the southernmost counties – evidence that points to heterogeneity in the model structure

333   within California.  The global coefficient and all the local coefficients for this variable are

334   positive – there is agreement between the two models on the direction of the influence of this

335   variable. Figure 3c shows a similar distribution in north-south direction of positive road density

336   coefficient. Figure 3d reveals the opposite for stream density coefficients, with larger values in

337   the north and smaller values in south. Contrary to our initial thoughts, stream density

338 demonstrated a negative relation to disease risk. This may reflect that flowing water is normally

339 not suitable for larval development of the various species of mosquitos that commonly transmit

340 WNV or that rasterizing the stream database into stream density introduces a component that is

341 not yet fully understood.

342      Our best ordinary least squares model, the global LSR model (equation 1) produced an

343 adjusted $R^2$ of 0.61 (p<0.05) with a corresponding corrected AIC of 567.70. Utilizing the same

344 environmental variables, our best local GWR model (equation 2) produced an adjusted $R^2$ of

345 0.71 (p<0.05) with a corresponding corrected AIC of 551.4. A 16 point decrease in the AIC and

346 approximately 16% improvement in the model performance suggest that incorporating spatial

347 data improves the predictive ability of WNV risk.

348

## Conclusions

349 **Conclusions**

350      One of the frequent technical issues in modeling disease risk is to incorporate local rather

351 than global associations in these models (Foley et al. 2009). In spatial regression models, a

352 global model can be used to examine the relationship between disease risk and potential

353 explanatory factors which are based on the assumption that the relationship is a stationary spatial

354 process (Miller 2012). For a small and homogenous region of interest, it is reasonable to assume

355 that the explanatory factors would not change significantly across the region, and the relationship

356 between WNV risk and the potential factors would also be unchanged. However, important

357 variables such as topography, climate, and population distribution change greatly when it comes

358 to a large region like California with an area of over 163,000 square miles. California is

359 geographically diverse and is equally varied in its range of climates with several climatic sub-

360    regions recognized. It would be unexpected to find that the spatial stationarity assumption holds

361    in such a large area.

362          The distinct north-south pattern revealed in our study could be attributable to typical

363    latitudinal expressions of temperature and precipitation, especially since California has a north-

364    south length of 1,350 kilometers. This environmental pattern is also a likely contributor to the

365    distribution of different mosquito species in the United Stated, especially notable in its

366    manifestation in California. A recent report (CDC 2013) shows that while *Cx. Tarsalis* is

367    distributed throughout California, *Cx. pipiens* is a more important mosquito vector in northern

368    California, while *Cx. quinquefasciatus* is more important in southern California. While WNV

369    can be found in a wide variety of ecosystems, the north-south pattern of infected birds detected

370    in this study may be expressed more noticeably in California due to the north-south differences

371    in mosquito species distributions as observed in the Centers for Disease Control report.

372          Our results concur that understanding WNV risks is improved when considering spatial

373    heterogeneity of the variables that affect the risk (Beck et al. 1994). Besides improving

374    prediction accuracy, spatial heterogeneity can also provide insights into the underlying

375    ecological processes controlling the distributions of vector populations and zoonotic pathogens

376    (Wimberly et al. 2008a) because GWR models consider spatial heterogeneity by separating the

377    large heterogeneous region into smaller, more homogeneous local regions. Fotheringham

378    (Fotheringham 2009a), stated that an advantage of using GWR is that it accounts for much of the

379    spatial autocorrelation in the residuals that is usually found in global modeling. Further, it is

380    possible that a variable that is insignificant at the global level might be important locally.

381          There are several limitations of this study. First, it is assumed that factors suitable for

382    mosquito habitat increase the likelihood of WNV spread in human populations. On the surface

383  this seems to be reasonably apparent; however, we do not have specific evidence that this is true.

384  Second, it is also assumed that the probability of human infection is higher in counties with

385  multiple confirmed WNV bird cases, another reasonable conjecture with several references in the

386  literature, but without direct confirmation. Potential problems with this assumption include

387  varying human population density (e.g. two areas with the same number of infected dead birds

388  reported but one area's human population density is substantially different than the other),

389  variations in level of public concern (as reports of infected dead birds increase, more people

390  begin looking for dead birds), and resource availability might bias the reporting of dead birds

391  (wealthy areas devote disproportionate resources to the issue). Thus, proper surveillance methods

392  that take into consideration these limitations while collecting infected dead bird data will

393  contribute to more meaningful results. Third, our approach assumes that people are infected

394  within the county of their residence, ignoring the possibility of contracting an infection while

395  traveling outside the county limits. Lastly, road density could also be correlated with dead bird

396  surveillance effort and might be a potential bias for reporting dead birds. We recognize that if

397  these assumptions do not hold, modeling WNV risks based on infected dead birds may yield

398  biased results. However, if the assumptions do hold, the local modeling approaches should

399  improve predictions of WNV risks.

400      The research described in this paper suggests that a spatially explicit local model using

401  GWR approaches to adjust for spatial autocorrelation and non-stationarity can yield improved

402  predictions compared to ordinary LSR modeling of WNV risk.  A spatially explicit modeling

403  technique may be useful in policy-making and decision-making depending on the granularity and

404  resolution of available data. Identifying the spatial variations in relationships by estimating local

405  regression parameters allows the spatial distribution and interaction of predictor variables to be

406    explored. Analyzing local variations in relationships provides those concerned with public health

407    policy the ability to target resources and to achieve improved outcomes through location-specific

408    activities (Comber et al. 2011) because spatial heterogeneity can improve predictions by

409    capturing geographic shifts in the ecological drivers (Wimberly et al. 2008a). While

410    environmental data used in this research were of fine resolution, WNV disease human incidence

411    data and infected dead bird data that is used is available only at a coarser county scale. We had to

412    assume that aggregating the environmental data up to the county adequately represented the

413    environmental conditions presented in the county, but we knew that data aggregation was likely

414    to introduce some uncertainty into the model. The dead bird model applied in this study can be

415    used for better understanding of WNV risk and the techniques used could be replicated at finer

416    spatial scales thus leading to better intervention efforts.

417          In summary, WNV, a globally emerging infectious disease, was found to be

418    heterogeneously related to environmental factors at the county level throughout California during

419    the time that our data were collected. Our findings may assist those conducting risk assessments

420    for WNV transmission in local areas by helping local public health entities allocate resources and

421    improve preparedness for an outbreak according to region-specific conditions.

422

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428

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563

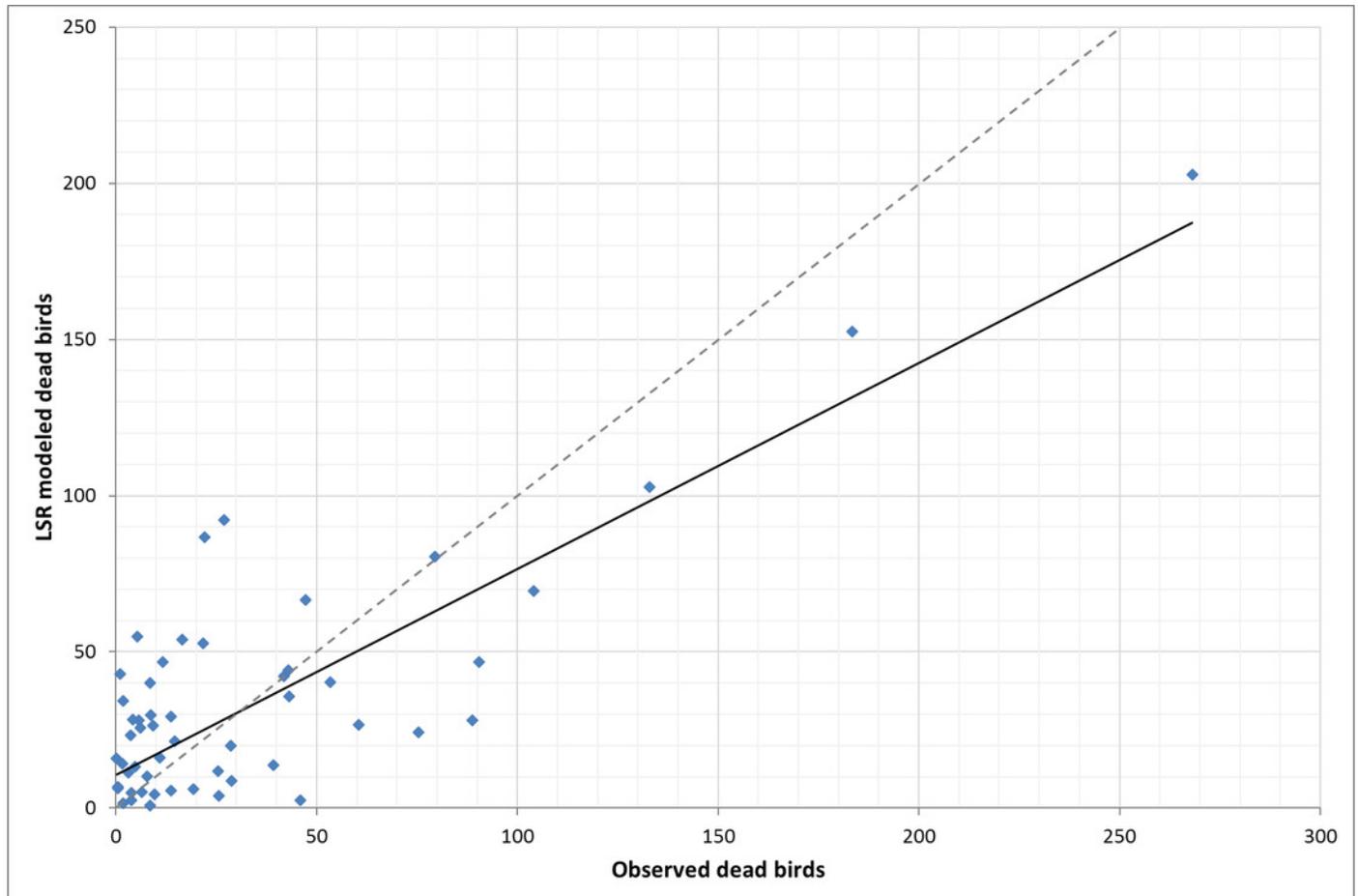
Environmental conditions related to WNV transmission risk.

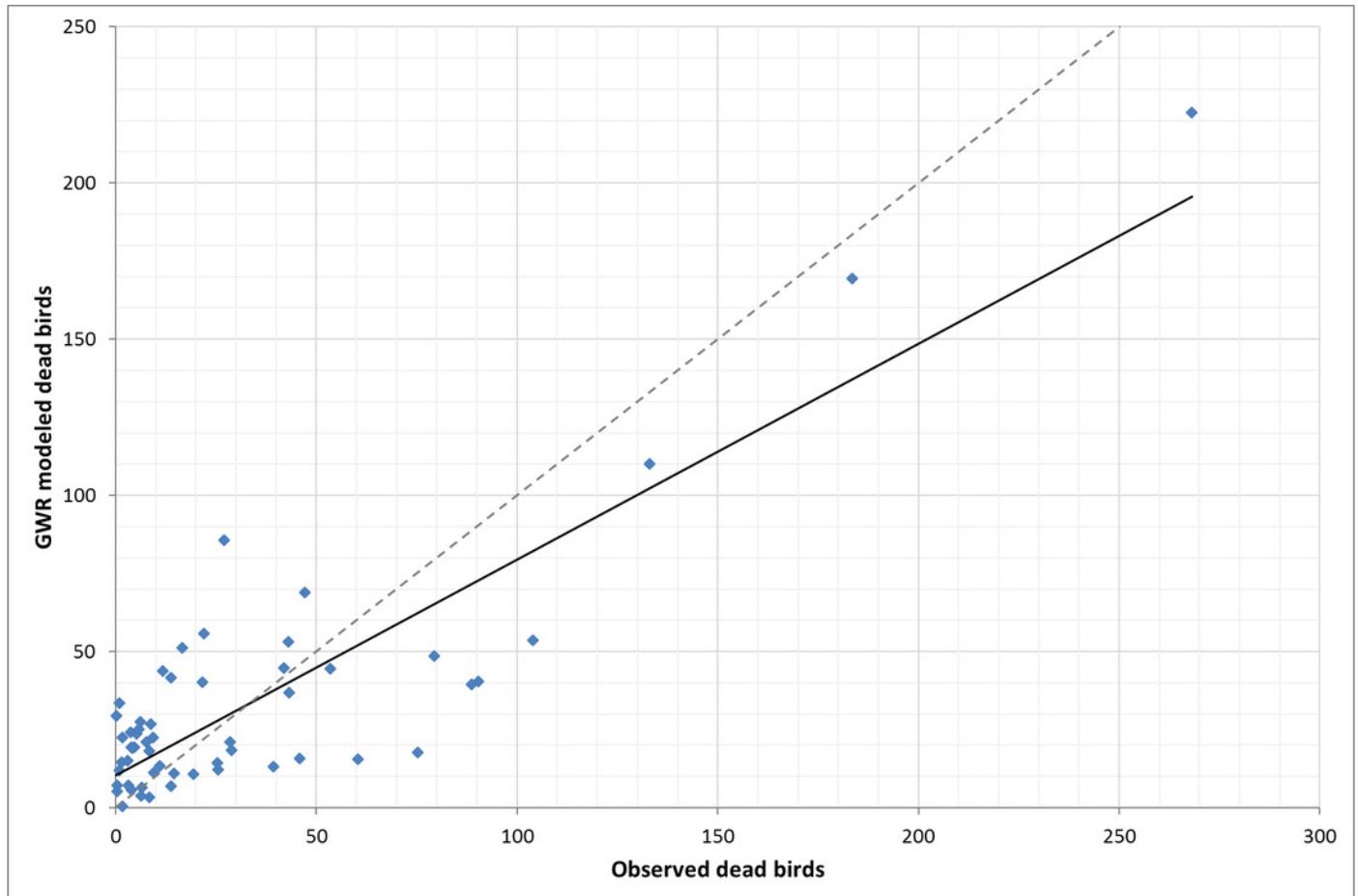
| Factors studied | Relation to WNV | References |
|---|---|---|
| Streams | Sites for breeding and resting | Cooke et al. 2006; Curtis et al. 2014; Schurich et al. 2014 |
| Temperature | Increases growth rate of vector, decreases egg development cycle and shortens extrinsic incubation period of vector | DeGroote et al. 2014; Kuehn 2012; Srivastava et al. 2001; Wimberly et al. 2008b |
| Surface slope | Water stagnation creating mosquito breeding ground | Cooke et al. 2006; Ozdenerol et al. 2008; Schurich et al. 2014; Srivastava et al. 2001 |
| Cultivated land | Linkage between habitat used and human-commensal nature of WNV mosquito vectors | Kilpatrick 2011 |
| Developed land | Linkage between habitat used and human-commensal nature of WNV mosquito vectors; warmer microclimates | Kilpatrick 2011 |
| Roads | Sites for breeding and resting along roadsides | Cooke et al. 2006 |
| Vegetation | Sites for breeding and resting. | Brownstein et al. 2002; Cooke et al. 2006; DeGroote et al. 2014; Ruiz et al. 2004a; Schurich et al. 2014; Srivastava et al. 2001 |
| Evapotranspiration | Related to the amount of moisture that is related to mosquito abundance | Liu and Weng 2012; Trawinski and Mackay 2008 |

Data sources.

| Data | Spatial resolution | Source |
|---|---|---|
| Elevation | 10m | National Elevation Dataset (NED) |
| LST | 1 Km | MODIS aboard the Terra and Aqua satellites |
| NDVI | 250 m | MODIS aboard the Terra and Aqua satellites |
| Evapotranspiration (ET) | 1 Km | MODIS aboard the Terra and Aqua satellites |
| Streams | available in vector format | U.S. bureau of reclamation |
| Roads | available in vector format | U.S. Census bureau |
| Cultivated land | 30 m | National Land Cover Database |
| Developed land | 30 m | National Land Cover Database |
| WNV infected dead birds count | County scale | U.S.G.S. National wildlife health center |
| WNV human incidence cases | County scale | U.S.G.S. National wildlife health center |
| Human population | County scale | U.S. Census bureau |

# Figure 1

Trendline plot for global LSR model (model: y = 0.6591x + 10.563; r2 = 0.66), dashed line ideal 1:1 relationship.

# Figure 2

Trendline plot for local GWR model (model: y = 0.6911x + 10.259; r2 = 0.75), dashed line ideal 1:1 relationship.

# Figure 3

Spatial distribution of (a) standardized residuals; (b) land surface temperature coefficients; (c) road density coefficients; (d) stream coefficients.