# AN ENSEMBLE SEASONAL FORECAST OF HUMAN CASES OF ST. LOUIS ENCEPHALITIS IN FLORIDA BASED ON SEASONAL HYDROLOGIC FORECASTS

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**Abstract.** We present a method for the ensemble seasonal prediction of human St. Louis encephalitis (SLE) incidence and SLE virus transmission in Florida. We combine empirical relationships between modeled land surface wetness and the incidence of human clinical cases of SLE and modeled land surface wetness and the occurrence of SLE virus transmission throughout south Florida with a previously developed method for generating ensemble, seasonal hydrologic forecasts. Retrospective seasonal forecasts of human SLE incidence are made for Indian River County, Florida, and forecast skill is demonstrated for 2–4 months. A sample seasonal forecast of human SLE incidence is presented. This study establishes the skill of a potential component of an operational SLE forecast system in south Florida, one that provides information well in advance of transmission and may enable early interventions that reduce transmission. Future development of this method and operational application of these forecasts are discussed. The methodology also will be applied to West Nile virus monitoring and forecasting.

## 1. Introduction

Recently, we developed an ensemble seasonal forecast of land surface wetness conditions in Indian River County, Florida (Shaman et al., 2003a). Three-month, seasonal forecasts of temperature and precipitation, as issued by the International Research Institute for Climate Prediction (IRI), were used to resample local historical meteorological conditions and generate ensemble forcing datasets for a TOPMODEL-based hydrology (TBH) model (Stieglitz et al., 1997; Shaman et al., 2002a). Retrospective forecasts were run, and forecast skill was demonstrated for mean area modeled water table depth (WTD), a measure of land surface wetness conditions. Both persistence of initial hydrologic conditions and the local skill of the IRI seasonal forecasts contributed to the local hydrologic forecast skill of modeled WTD in Florida (Shaman et al., 2003a).

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This forecast methodology was created in anticipation of developing an ensemble seasonal forecast of mosquito-borne disease transmission. Previously, we documented an association between antecedent drought, near-coincident wetting and transmission of SLE virus, a mosquito-borne pathogen (Shaman et al., 2002b). We used the TBH hydrology model to hindcast mean area WTD in Indian River County, Florida, and compared these model simulations to levels of SLE virus transmission to sentinel chickens maintained in flocks throughout south Florida. Transmission of the SLE virus was found to be strongly associated with drought 17 weeks prior and wetting conditions 2 weeks prior (Shaman et al., 2002b).

A mechanism for this empirical relationship was suggested by mosquito collection data, also taken in Indian River County. In Florida, extreme droughts typically occur during the spring. Mosquito collection data indicated that during such droughts *Culex nigripalpus* Theobald, the principal SLE virus vector (Chamberlain et al., 1964; Dow et al., 1964; Shroyer, 1991), is more abundant in densely vegetated, humid habitats. Rather than indicate an increase in mosquito abundance, these data suggest that drought restricts *Cx. nigripalpus* flight and host seeking activity to these woodland habitats, which are also used by nesting wild birds (Shaman et al., 2002b). Wild birds are the zoonotic amplification hosts of SLE virus in Florida. Consequently, drought drives *Cx. nigripalpus*, avian hosts, and SLE virus into contact with one another. This forced interaction of vector mosquitoes and avian hosts drives the rapid epizootic amplification of SLE virus, such that both bird and mosquito SLE virus infection rates increase substantially. Subsequently, when the drought ends and water resources increase, the infected mosquitoes and birds disperse. It is at this point that transmission to other organisms, most notably sentinel chickens and humans, begins.

A similar association between drought, wetting and the presence of SLE hemagglutination inhibition (HI) antibodies in wild birds has also been shown (Shaman et al., 2003b). More recently, we shifted our focus to human SLE incidence in south-central Florida. We examined the record of human cases of SLE from 1990 to 1998 for all Florida counties lying partially or wholly between 26.5N and 29N. Using available records from meteorological stations in these counties, we forced the TBH model and retrospectively simulated surface wetness conditions in the area of each station. As for both SLE virus transmission to sentinel chickens and SLE HI antibody seroprevalence in wild birds, we found a statistically significant empirical association between low modeled WTD (drought) 4 months prior, higher modeled WTD (wetting) one-half month prior, and human SLE incidence (Shaman et al., 2004).

Here we combine this relationship between modeled WTD and human SLE incidence with the ensemble seasonal forecasts of land surface wetness conditions. In addition, we expand our analysis of SLE virus transmission as measured by sentinel chickens to all of south Florida and combine this newly derived empirical relationship with the ensemble seasonal forecasts of land surface wetness conditions. Seasonal retrospective forecasts of both human SLE incidence and SLE virus transmission to sentinel chickens throughout south Florida are made for 1999–2003 and their skill is examined. An example real-time forecast is also presented.

## 2. Model and Data

Hydrologic modeling follows the methods set forth in Shaman et al. (2002a, 2003a). We use the TBH model to simulate variations in water table depth (WTD) at 14 sites in 8 counties in south Florida (Table I). The TBH model was calibrated and validated at the Vero Beach site as previously described (Shaman et al., 2002a, 2003a). Soil and vegetation types were derived from U.S. Department of Agriculture sources. Simulations at all other station sites, most of which lack local validation data, were performed using the calibrations established at the Vero Beach site. Most of south Florida has similar flat topography, similar tropical vegetation and is subject to channelization and water control. While some inaccuracies are no doubt introduced, these commonalities among the sites permit this regional validation and application of the TBH model to all 14 station sites.

The TBH model combines a soil column, which simulates the vertical movement of water and heat within the soil and between the soil surface, vegetation and the atmosphere, with the TOPMODEL approach (Beven and Kirkby, 1979), which incorporates the statistics of topography to track the horizontal movement of shallow groundwater from the uplands to the lowlands. Seven hourly meteorological

TABLE I
List of the 14 station sites used in this study. All daily precipitation and temperature records employed are for 1950–2003, except where marked by ‘a’ (1949–2003) and ‘b’ (1966–2003)

| Station site | County | Latitude | Longitude |
|---|---|---|---|
| Bartow | Polk | 27.90°N | 81.85°W |
| Belle Glade | Palm Beach | 26.68°N | 80.67°W |
| Canal Point | Palm Beach | 26.92°N | 80.63°W |
| Fort Myers | Lee | 26.58°N | 81.92°W |
| Mountain Lake | Polk | 27.93°N | 81.60°W |
| Myakka River | Sarasota | 27.25°N | 82.32°W |
| Naples | Collier | 26.17°N | 81.72°W |
| Plant City[a] | Hillsborough | 28.02°N | 82.15°W |
| Punta Gorda[b] | Charlotte | 26.92°N | 82.00°W |
| Tampa[a] | Hillsborough | 27.67°N | 82.53°W |
| Venice | Sarasota | 27.10°N | 82.43°W |
| Vero Beach 4SE[a] | Indian River | 27.65°N | 80.40°W |
| West Palm Beach | Palm Beach | 26.68°N | 80.10°W |
| Winter Haven | Polk | 28.02°N | 81.73°W |

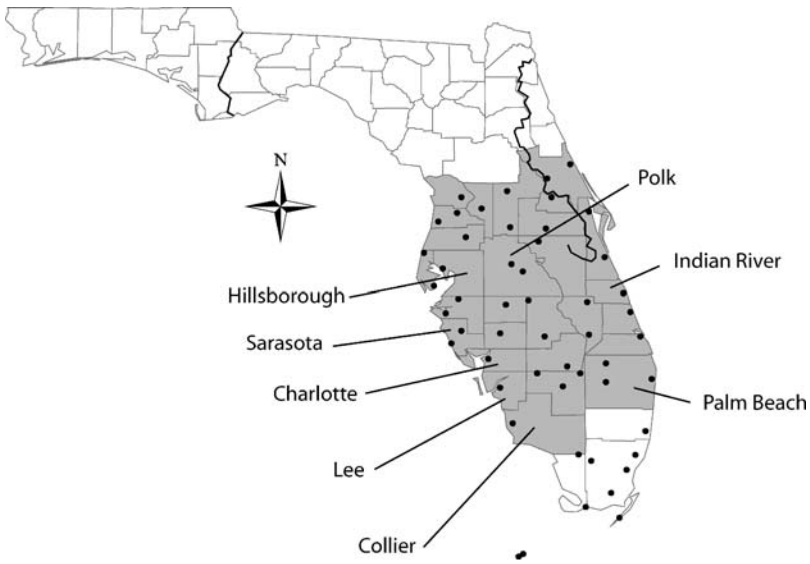


*Figure 1.* Map of south Florida. The 28 counties previously used to derive Equation (1) (Shaman et al., 2004) are shaded; dots represent the 42 meteorological station sites within these counties. The three southernmost counties and their additional 10 meteorological station sites were included in the analyses of SLE virus transmission to sentinel chickens reported here. The eight counties (with a total of 14 station sites) used for ensemble seasonal forecast are labeled.

variables – precipitation, temperature, surface pressure, wind speed, mixing ratio, incident solar radiation and downwelling longwave radiation – are needed to force the TBH model. Because hourly data is of limited availability we use daily precipitation and temperature data and a resampling procedure (Shaman et al., 2003a) to generate the hourly forcing data sets. Daily precipitation and temperature data were assembled from National Climate Data Center (NCDC) archives for all stations with near complete daily records of precipitation and temperature spanning 1988–2003 ($>$80% complete) for 31 south Florida counties. Gaps in the daily records were filled with data from adjacent stations. A total of 52 records of 1988–2003 daily data were assembled (Figure 1).

The hourly meteorological data used for the resampling procedure were assembled from National Climate Data Center (NCDC) archives for Vero Beach, Florida. Gaps in the hourly Vero Beach record were filled with hourly data from NCDC archives for Melbourne and West Palm Beach, Florida. In addition, hourly meteorological data were assembled from the NCDC Solar and Meteorological Surface Observation Network (SAMSON) dataset for Daytona Beach, Miami, Tampa and West Palm Beach. For the Vero Beach hourly record, solar radiation data were provided by the Northeast Regional Climate Center (NRCC) from analysis of the NCDC data using the NRCC solar energy model (DeGaetano et al., 1995). Solar radiation data are included in the SAMSON dataset. Using the closest hourly meteorological record (Daytona Beach, Miami, Tampa, Vero Beach or West Palm Beach) and the resampling procedure (Shaman et al., 2003b), hourly forcing data sets were then created for each of the 52 station sites.

Summaries of mosquito-borne arboviral human case data are compiled, analyzed, and reported weekly, monthly, and annually by the Florida Department of Health, Tallahassee, Florida. For this work, we used the 1999–2003 monthly human SLE cases as reported by county for south Florida. We define human SLE incidence as a categorical variable: one, if one or more human SLE cases were recorded within a given county for a given month; zero, if no cases were recorded. With the exception of epidemic years (e.g., 1977, 1990), human SLE cases are rare in Florida. Only three cases of human SLE were recorded during the period of this study, 1999–2003. These cases occurred in Charlotte (October 1999), Lee (October 1999), and Sarasota (September 1999) counties.

For the SLE virus transmission data we used records from 196 different sentinel chicken flocks maintained in 25 South Florida counties. Generally, a 1.0 ml blood sample was drawn weekly from each bird during peak transmission periods (July through November) and twice a month during the rest of the year. Serum samples were assayed for Flavivirus and Alphavirus hemagglutination inhibition (HI) antibodies. Arbovirus-positive HI serum samples were confirmed to species by IgM ELISA and plaque reduction neutralization tests at the Florida Department of Health and Rehabilitative Services (FDHRS), Tampa Branch Laboratory. All arboviral-positive sentinel chickens were immediately replaced with baseline-negative birds. Most flocks were replaced with baseline-negative birds each May (Day and Stark, 1996).

## 3. Forecast Methodology and Analysis

The best-fit logistic regression model ($p < 0.0001$) relating antecedent drought, near-coincident wetting and human SLE incidence is (Shaman et al., 2004):

$$P(\text{SLE}) = (1 + \exp(10.40 + 6.05 \times \text{WTD}_4 - 0.67 \times \text{WTD}_{0.5}))^{-1} \tag{1}$$

where $P(\text{SLE})$ is the probability of human SLE incidence, $\text{WTD}_4$ is the half-monthly mean WTD 4 months prior, and $\text{WTD}_{0.5}$ is the half-monthly mean WTD one-half month prior. We use this relationship to create ensemble forecasts of human SLE incidence. We combine the model (Equation (1)) with ensemble seasonal forecasts of WTD made using the TBH model.

Ensemble retrospective 3-month forecasts of WTD were made for all seasonal forecasts issued by the IRI during 1999–2003 for the area containing each of the 14 station sites (448 ensemble forecasts in total). Each member of each 500-member ensemble forecast was produced by forcing the TBH model with observed meteorological data up to the point of forecast, then a 3-month forecast meteorological record that was selected from a distribution of records delineated by the IRI seasonal forecast. These ensemble forecasts were then combined with the empirical model established in south Florida for 1990–1998, i.e., Equation (1). Thus, we establish the model for south Florida during one time period (1990–1998), and test the skill of the ensemble forecasts for another (1999–2003).

Each ensemble forecast contains a distribution of 500 predictions of the probability of one or more human cases of SLE occurring in a local county over a 3-month period. The forecast of WTD predicts wetness for the immediate next 3 months; the ensemble forecast of human SLE incidence gives predictions for 2–4 months (e.g., an ensemble seasonal forecast of WTD for January–March would predict human SLE incidence for February–April). Predictions for the first month (e.g., January in our example) were also made using Equation (1) and the single realization of modeled WTD leading up to forecast period (e.g., observed meteorological data for the preceding September–December in our example).

Forecast skill was assessed formally using the Brier Skill Score (Wilks, 1995), see appendix for details. As in climate and weather forecast, skill refers to the accuracy of a forecast or set of forecasts relative to a standard or climatology. Here the climatology consists of 12 monthly values, each the historical probability that human SLE incidence occurred in a county lying partially or wholly between 26.5N and 29N in south Florida for a given month during 1990–1998.

## 4. Sentinel Chicken Record Analysis

We defined dichotomous categories of monthly transmission of SLE virus to sentinel chickens within a county as: one if greater than a cutoff percentage of posted chickens tested positive for SLE virus antibodies; zero if less than (or equal to) the cutoff percentage of posted chickens tested positive for SLE virus antibodies. The cutoffs tested were 0% (i.e., whether any chickens tested positive), 10, 20, and 30%. Increasing cutoff percentages reflect greater transmission activity.

Bivariate logistic regression analysis was then used to associate the probability of these countywide dichotomous categories of 1990–1998 SLE virus transmission to sentinel chickens with lag combinations of average monthly modeled WTD at each station site within the county. All counties were analyzed in aggregate. Whole model goodness-of-fit was measured by log-likelihood ratio and the pseudo $r$-squared (uncertainty) coefficient. Individual parameter estimates were made using a maximum likelihood procedure; Wald chi-square tests were used to determine whether these estimates were significantly different from zero. The best-fit logistic regression model equations were then combined with the ensemble seasonal forecasts in fashion similar to that described above for human SLE incidence, and forecast skill was assessed for 1999–2003 using the Brier Skill Score (Wilks, 1995; appendix).

TABLE II
Brier Skill Score assessment of all 448 seasonal retrospective ensemble forecasts of human SLE incidence

| | Human SLE incidence | |
|---|---|---|
| Time period | Skill score | Significance |
| First month | −0.10 | NS |
| Second month | 0.22 | $p < 0.001$ |
| Third month | 0.13 | $p < 0.001$ |
| Fourth month | 0.04 | $p < 0.001$ |

NS = not significant.

## 5. Results

### 5.1. HUMAN SLE INCIDENCE FORECAST

Skill scores calculated for the 448 retrospective forecasts of human SLE incidence in the period 1999–2003 are shown in Table II. No skill was found for the single realization first-month forecasts, but skill for months 2–4 is statistically significant ($p < 0.001$) as shown by a Monte Carlo procedure, described in the appendix. Skill at months 2 and 3 is quite high (0.22; 0.13); skill at month 4 is marginal (0.04). That is, these forecasts provide a more accurate prediction of the probability of human SLE incidence than a prediction based only on historically observed frequency.

Table III presents a breakdown Brier skill scores on a site-by-site basis. There is considerable variability among the sites; some stations display high skill, while others have none. Biases due to the regional calibrations of the TBH model may have corrupted some station site forecasts. This distribution of skill scores in aggregate yields the overall skill scores shown in Table II. Of the four station sites within counties that had human SLE incidence during 1999, two of the four stations (Myakka River and Venice) predict a higher likelihood of SLE during the month and in the county when it does indeed occur (data not shown).

We present a sample forecast of human SLE incidence in Indian River County. TBH model ensemble forecasts for August–October 2003 were combined with Equation (1) and are presented in Figure 2. Ensemble forecasts are given for September–November 2003. Confidence intervals, based on logistic regression model standard error, are provided for the single realization August 2003 forecast. For all 4 forecast months, the probability of human SLE incidence is less than would be expected from climatology. No human cases of SLE were reported in Indian River County for this period.

TABLE III
Brier Skill Score assessments of the seasonal retrospective ensemble forecasts of human SLE incidence at each station site

| Station site | Number of forecasts | First month | Second month | Third month | Fourth month |
|---|---|---|---|---|---|
| Bartow | 35 | −0.25 | **0.08** | **0.03** | −0.08 |
| Belle Glade | 36 | **0.50** | **0.44** | **0.46** | **0.70** |
| Canal Point | 36 | **0.42** | **0.31** | **0.35** | **0.73** |
| Fort Myers | 36 | −0.22 | −0.46 | −0.30 | −0.16 |
| Mountain Lake | 35 | −1.26 | −0.84 | −0.53 | −0.44 |
| Myakka River | 28 | **0.38** | **0.42** | **0.08** | **0.62** |
| Naples | 34 | −0.09 | **0.48** | **0.34** | **0.48** |
| Plant City | 28 | **0.18** | **0.38** | **0.20** | **0.38** |
| Punta Gorda | 28 | −0.19 | 0.22 | 0.10 | −0.17 |
| Tampa | 26 | **0.14** | **0.51** | **0.27** | **0.49** |
| Venice | 28 | −0.39 | −0.47 | **0.08** | **0.19** |
| Vero Beach | 35 | **0.70** | **0.80** | **0.83** | **0.81** |
| West Palm Beach | 36 | **0.67** | **0.62** | **0.63** | **0.63** |
| Winter Haven | 27 | **0.54** | **0.75** | **0.78** | **0.81** |

Values significant at $p < 0.01$ are in bold.

### 5.2. SLE VIRUS TRANSMISSION ANALYSIS AND ENSEMBLE FORECAST

We next turn to analysis of the sentinel chicken record of the 1990–1998 SLE virus transmission in south Florida. SLE virus transmission to sentinel chickens is more common than human SLE incidence and thus provides a larger sample of events. Table IV shows the best-fit results of logistic regression analysis with the 4 dichotomous categories of SLE virus transmission. We present only the best-fit results, but in fact a range of time lags was found to be significantly associated with SLE virus transmission to sentinel chickens (data not shown). This range of time lags reflects the slow variability of land surface wetness conditions and is consistent with previous findings (Shaman et al., 2002b, 2003b, 2004). The best-fit models demonstrate that wetter local conditions in the preceding month are significantly associated with an increased probability of SLE virus transmission to sentinel chickens. Antecedent drought conditions in the 3–4 preceding months are also significantly associated with an increased probability of SLE virus transmission to the sentinel chickens in south Florida. These empirical models depicting drought followed by wetting then SLE virus transmission are consistent with previous findings for SLE virus transmission in Indian River County, Florida (Shaman et al., 2002b), the presence of SLE hemagglutination inhibition (HI) antibodies in wild birds in Indian River County (Shaman et al., 2003b) and human SLE incidence throughout south Florida (Shaman et al., 2004).

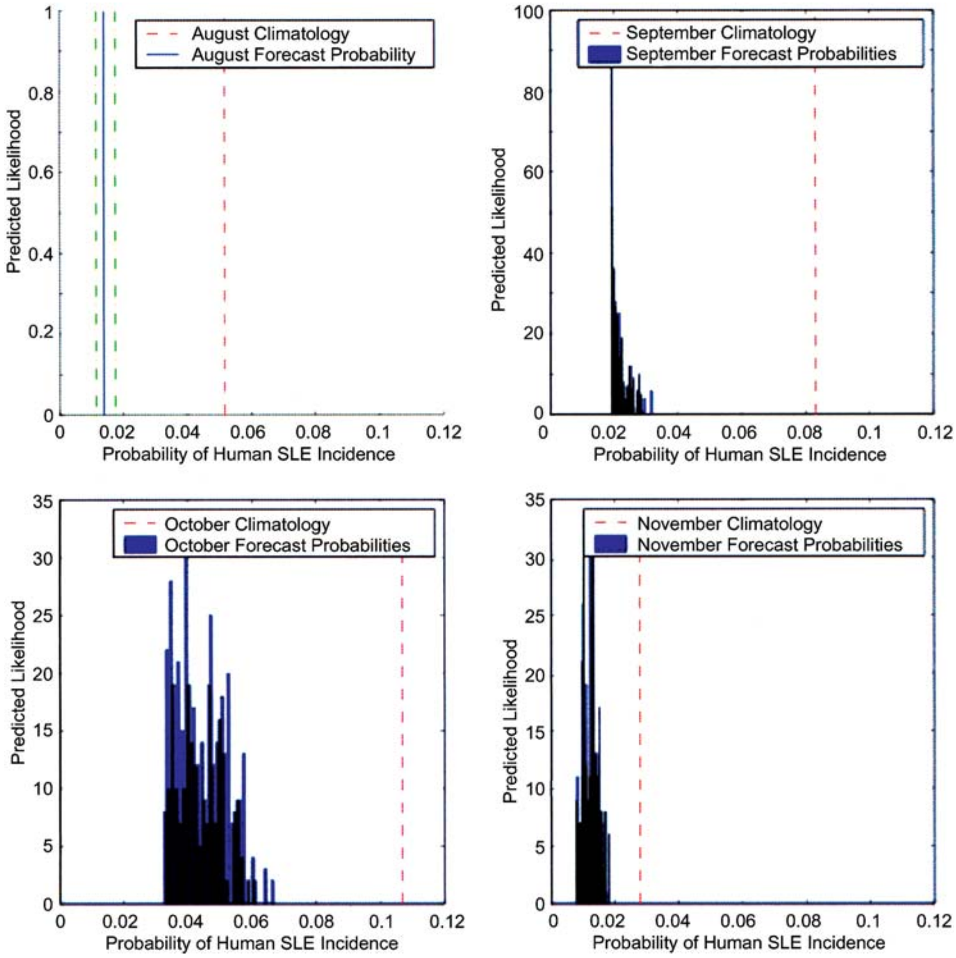


*Figure 2*. Real-time monthly forecasts of human SLE incidence in Indian River County, Florida. Ensemble forecasts are presented for months 2–4 (September–November 2003). Dashed lines are climatology. Confidence intervals (the dash-dot lines) based on logistic regression model error estimates are given for month 1 (August 2003).

The equations presented in Table IV were next combined with the ensemble seasonal forecasts for 1999–2003. Brier Skill Scores are shown in Table V. Similar to the human SLE incidence forecasts, there is generally skill for months 2–4. There is also considerable variability among the sites with some stations displaying high skill and others none (data not shown). The Brier Skill Scores improve with increasing cutoff transmission percentage. This improvement is due in part to the reduced sensitivity to drought of the >0% transmission category, which is seen in the comparatively lower Lag 1 slope estimate, and indicates the empiric models are better at distinguishing larger transmission events. This implies that epidemic transmission will be more accurately forecast than sporadic transmission.

TABLE IV

Best-fit empirical relationships based on bivariate logistic regression analyses of dichotomous categories of percentage of posted sentinel chickens testing seropositive for HI antibodies to SLE virus (1990–1998) on month lags of modeled WTD as simulated by the TBH model at each station site within the county

| Dichotomous predictand | Lag 1 | Lag 2 | Intercept | Lag 1 slope | Lag 2 slope |
|---|---|---|---|---|---|
| >0% | 4 | 1 | 2.28 | 2.10 | −1.25 |
| >10% | 4 | 1 | 4.86 | 3.52 | −1.23 |
| >20% | 3 | 1 | 5.64 | 3.51 | −1.06 |
| >30% | 3 | 1 | 6.39 | 3.57 | −0.88 |

*Note*. All 25 south Florida counties with sentinel chickens posted (during 1990–1998) were analyzed in aggregate. The lags are given in months. In all cases, the whole model fit based on log-likelihood ratio is significant at $p < 0.0001$. Equations predicting the probability of SLE virus transmission based on these best-fit relationships have the same form as Equation (1).

TABLE V

Prediction of the level of monthly transmission as measured by sentinel chickens

| | Dichotomous criterion (% Seroconversion) | | | |
|---|---|---|---|---|
| Forecast month | >0% | >10% | >20% | >30% |
| First | −0.13 (18) | −0.13 (8) | −0.04 (4) | **0.23** (1) |
| Second | −0.03 (21) | **0.11** (2) | **0.29** (0) | **0.38** (0) |
| Third | **0.09** (27) | **0.23** (1) | **0.30** (1) | **0.51** (0) |
| Fourth | **0.07** (17) | **0.13** (7) | **0.14** (4) | **0.36** (1) |

*Note*. Brier Skill Score assessment of all 448 seasonal retrospective ensemble forecasts of SLE virus transmission to sentinel chickens for 14 sites in 8 counties. The number of forecast period months (first, second, third, fourth) for which both a forecast and sentinel chicken validation data existed are 311, 318, 323 and 311, respectively. Bold values are significant at $p < 0.01$. The number of times a forecast period month exceeded the dichotomous criterion (i.e., >0% seroconversion, >10% seroconversion, etc.) is shown in parenthesis.

## 6. Discussion

This study presents a new methodology for seasonal disease forecast. We have combined an ensemble seasonal forecast of WTD with an empirical model relating modeled WTD and human SLE incidence and a new empirical model relating modeled WTD and SLE virus transmission to sentinel chickens. The skill of these seasonal disease forecasts has been explored and demonstrated in aggregate for months 2–4. A sample forecast has also been presented.

Within the empirical models, antecedent drought (i.e., WTD 3–4 months prior) is the much stronger determinant of human SLE incidence and SLE virus transmission (see Equation (1) and Table IV parameter estimates). Because the IRI forecasts used in this study are seasonal (3 months), usually only the near-coincident wetting lag is determined by the distribution of the ensemble forecast of WTD. In fact, a drought lag greater than 3 months predates all of the forecast period and is based exclusively on observations. Consequently, it is the same for all members of an ensemble forecast. Thus, the probability of human SLE incidence or SLE virus transmission is usually constrained by a single value for the antecedent drought lag but a distribution of values for the near-coincident wetting lag.

The forecasts assume that the empiric models relating drought, wetting and human SLE incidence or SLEV transmission are stationary from 1990 to 1998, the period in which the relationship is derived, through 1999–2003, when the forecasts are evaluated. This assumption appears to be true; logistic regression of the 1999–2003 data on modeled conditions throughout south Florida for that period produces the same basic best-fit relationships and very similar parameter estimates (data not shown). Given this stationarity, 2 other sources of error can corrupt the seasonal forecasts. Firstly, from the empiric model both Type I and Type II error are still possible. We have previously examined the occurrence of missed positives and shown that antecedent drought is nearly always associated with human SLE incidence (Shaman et al., 2004). False positives within the empiric model occur more frequently (data not shown) and introduce more error. The second source of error comes from the seasonal forecasts of WTD, which themselves are not always accurate. Together these errors (Type I, Type II and inaccuracy of the seasonal forecasts of WTD) corrupt the skill of the forecasts.

The skill that does exist for months 2–4 indicates that these errors do not overwhelm the coupled prediction system and that the forecasts remain more accurate than climatology. On the other hand, the lack of skill for the first month is of concern. It may reflect a smaller sample size (i.e., the first month is the result of a single model realization, whereas months 2–4 are based on 500-member ensemble future predictions of WTD), local inaccuracies or biases in the TBH model, or an excess of Type I or Type II errors. We are currently exploring these possibilities.

### 6.1. DETECTING HUMAN SLE INCIDENCE AND SLE VIRUS TRANSMISSION

There is considerable spatial heterogeneity of land surface wetness conditions in south Florida; so much so that wetness conditions can differ radically within ten kilometers (Shaman et al., 2004: Figures 2–6). The network of meteorological stations from which we force the TBH model and forecast human SLE incidence is generally spaced at distances greater than ten kilometers (Figure 1). This sparse distribution of meteorological stations makes it more difficult to detect sporadic SLE transmission such as that observed in 1999–2003. When SLE transmission takes place at high levels over a large geographic area, such as the 1990 SLE epidemic, the necessary drought and wetting conditions are broadly pervasive and are readily detected, even by the sparse network of meteorological stations.

Historically in Florida, widespread epidemics of SLE have occurred followed by years of little or no human SLE disease incidence. Drought appears to be a necessary precondition, producing the amplification and increased mosquito infection rates that put humans at greater risk of SLE during subsequent wetting events. While hydrologic conditions predict whether amplification and transmission are favored, hydrology is not the sole determinant of human SLE incidence. Mosquito and amplification host population levels and age structures, prior exposure of birds and humans to the pathogen, as well as human activity, including outdoor activity in mosquito habitats, all play a role in determining human exposure to biting infectious mosquitoes. Furthermore, even at very low mosquito infection rates, it is still possible for a human to come in contact with an SLE-infected mosquito, be bitten, infected, and develop clinical symptoms. All these factors make prediction of human SLE incidence, particularly low levels of human SLE incidence, such as the 'sporadic' episode recorded in 1999, very difficult.

Previous findings (Day and Curtis, 1999; Day and Stark, 1999; Shaman et al., 2002a, 2003a) suggest that three factors conspire to create an SLE epidemic: 1) a large population of susceptible wild birds; 2) severe springtime drought that facilitates amplification of the SLE virus among vector mosquitoes and a portion of the local wild bird population, and; 3) continued rainfall and wetting of the land surface in the summer and early fall, which sustains a large, active vector population. In the future, a more complete forecast model of human SLE incidence might integrate information regarding the dynamics of wild avian hosts, mosquito vector, and virus.

For instance, wild bird populations can be monitored placing special emphasis on annual reproductive success and the proportion of a local avian population that is susceptible and able to amplify virus. Wild birds are crucial for the amplification of mosquito-borne arboviruses. A high viral prevalence in local wild bird populations precedes human cases of SLE by several months (Day and Stark, 1996). If a sufficient time series of SLE viral prevalence in wild birds could be documented, its association with human SLE incidence could be determined, and if significant, its effect added to the forecast model. Unlike the sentinel chickens, which measure viral transmission after amplification, wild birds are directly involved in amplification and aid prediction by further constraining SLE transmission risk before it occurs.

At present, sampling of wild bird infection rates is labor intensive and costly; most counties in Florida do not perform this routinely. Meteorological data, however, is widely available throughout the state. Operational application of the TBH model and the ensemble forecast procedure could be centrally handled at the state level or by each of Florida's five water management districts. These results could then be passed to the Florida Department of Health for response.

### 6.2. USE OF THE FORECASTS

The forecasts predict tendencies for more or less disease incidence and transmission. If the empiric relationship (Equation (1)) found between modeled hydrologic conditions and human SLE incidence is stationary, these predicted tendencies will be robust and provide a more skillful forecast than climatology. However, these forecasts are probabilistic, not deterministic. While the success of an individual forecast can be striking, it yet accounts for only a single realization. Just as a strong El Niño does not necessitate landslides in northern California (but does indicate a higher chance of torrential rains in the area), and as a weather forecast indicating a 60% chance of precipitation does not guarantee rainfall, a higher or lower than predicted probability of human SLE incidence within a county does not predict a definite outcome.

The question then arises of how to use the forecasts. A Brier Skill Score of 1 indicates a perfect forecast, one that is always more accurate than the comparison climatology. Such high skill scores are not evident here. However, where the Brier Skill Scores are positive, though less than 1, and significant one may expect that on average over many realizations the forecast model predictions will be more accurate than climatology. A higher skill score reflects greater accuracy. These facts suggest that the forecast model presented here could be used for the periods of demonstrated skill (forecast months 2–4). For instance, given their 3–4 month lead, low transmission risk forecasts might allow counties to reduce mosquito pool testing, the number of sentinel chickens posted, the frequency of bleedings, or even mosquito spraying. Resources could then be conserved for less certain years.

A complication arises from the fact that climatology (i.e., historical seasonal likelihoods of human SLE incidence and SLE virus transmission) currently is not the sole information used by public health officials for deciding where and when to attempt SLE control. Public health officials also sample the environment by testing mosquito pools for SLE virus. In addition, the sentinel chickens provide near real-time measures (1–2 week delay) of where SLE virus transmission is occurring, and control efforts are directed accordingly. It remains to be determined whether it is more effective to expend resources based on the present surveillance system (seasonal likelihoods, and near real-time assays of SLE virus transmission based on mosquito pools and sentinel chickens), the forecasts presented here, which indicate 2–4 months beforehand the probability of where and when SLE virus transmission will occur, or a combination of both. The cost-benefit analysis needed to examine this issue quantitatively is beyond the scope of the present paper.

However, it may be worthwhile to dedicate a portion of public health resources to controlling mosquitoes during local spring droughts, when important vector species are localized within hammock environments and SLE virus levels are amplifying. Currently, public health officials chase virus activity, putting control in effect in areas where transmission is already evident. It may prove more effective to control the mosquitoes during amplification prior to transmission. This is where information derived from the skillful ensemble seasonal forecasts presented here might prove useful. These forecasts would define the areas most likely to suffer SLE virus transmission in the coming months – areas currently undergoing amplification in focal habitats. Mosquito control could then be focused in these environments prior to human transmission.

Presently, most Florida counties have ongoing mosquito and biting fly control programs from May through November. These include larvicide and adulticide control efforts on a regularly scheduled basis. Some counties, like Collier and Lee, are at maximum control effort many months of the year. A sharp increase in sentinel chicken seroconversion rates generally translates into an increased vector control effort, usually in the form of aerial adulticiding. This happened in most Florida counties during 1990, 1993, and 1997. Early season vector control efforts, however, are usually reduced in most counties during the amplification phase (April–June) of the annual arboviral transmission cycle. This reduced control allows efficient arboviral amplification during years of drought. Major vector control efforts in Indian River County during the 1990 SLE epidemic came well after the infection dates for most of the reported human cases (Day, 1991). Likewise, major vector control efforts in Indian River County during 1993 and 1997 came late in the year (September and October), well after amplification. In Florida, and in other regions of the country where mosquito-borne arboviral epidemics are reported, increased vector control efforts generally come too late in the year to impact virus amplification and subsequent transmission to humans. The number of human cases in a region depends directly on the number of infected mosquitoes, which are indicated after amplification by sentinel chicken seroconversion rates. The major difference between an epidemic year (1990) and a focal (1993) or sporadic (1997) transmission year is the efficiency of amplification which is reflected by the number of infected mosquitoes. Once amplification levels sufficient to initiate an epidemic have been realized, vector control may reduce human cases, but epidemic transmission to humans generally continues, as was observed during the 1990 SLE epidemic in south Florida. The only hope of truly mitigating an epidemic is to initiate a massive, targeted vector control effort during the arboviral amplification phase of the transmission cycle.

At present, West Nile virus (WNV) is of great public health concern. Since its introduction in New York City in 1999, WNV has spread across the continental United States entering Florida in 2001. WNV and SLE share similar zoonoses and transmission dynamics. We recently compiled the 3 years of incidence data (among both humans and sentinel chickens) by county in south Florida (2001–2003) and found a similar relationship between the hydrologic conditions driving SLE and WNV transmission (Shaman et al., 2005). Unfortunately, having established this relationship for WNV and because of the short period of time the virus has been in Florida, there is yet no further data with which to perform retrospective forecasts; however, SLE is a good analogue for WNV. This paper establishes the methodology for making such forecasts and verifying their forecast skill. We are currently performing such real-time monitoring and forecasting in south Florida for both SLE and WNV and making these results available to state officials.

## Appendix

The Brier Score is designed for use with a probabilistic forecast of a dichotomous predictand (i.e., there was or was not human SLE incidence), and is calculated:

$$\mathrm{fBS}_t = \frac{1}{n}\sum_{k=1}^{n}(F_{kt} - O_t)^2 \tag{A1}$$

where $\mathrm{fBS}_t$ is the forecast Brier Score for seasonal forecast month $t$, $n$ is the number of members of a forecast ensemble, $F_{kt}$ is the forecast probability of human SLE incidence as predicted for seasonal forecast month $t$ and ensemble member $k$, $O_t$ is the observation of whether human SLE incidence took place during seasonal forecast month $t$ ($O_t = 1$ if one or more human cases occurred; $O_t = 0$ no human cases occurred). Similarly,

$$\mathrm{cBS}_t = \frac{1}{n}\sum_{k=1}^{n}(C_t - O_t)^2 \tag{A2}$$

where $\mathrm{cBS}_t$ is the climatological Brier Score, and $C_t$ is the climatological probability of human SLE incidence for seasonal forecast month $t$. The climatological probability for each month was the percentage of times human SLE incidence occurred for that month in each of the 28 south Florida counties during 1990–1998.

The skill score (SS) is computed directly from the Brier Scores

$$\mathrm{SS} = 1 - \frac{1}{m}\sum_{t=1}^{m}\left(\frac{\mathrm{fBS}_t}{\mathrm{cBS}_t}\right) \tag{A3}$$

where $m$ is the number of seasonal forecasts. A skill score of 0 represents no improvement of forecast skill relative to climatology. A skill score greater than 0 demonstrates improvement of the forecast relative to climatology; a skill score of 1 is a perfect forecast.

Bootstrap confidence intervals were estimated using a Monte Carlo procedure. The null hypothesis is that the forecasts have no greater skill than one generated randomly from modeled WTD climatology. These ensemble forecasts were simulated by randomly selecting half-monthly modeled WTD values among the years of a 1949–1998 simulation record at the respective site of forecast. 1000 such forecasts were made and a mock SS was calculated for each. From this distribution of mock SS values, significance of the actual SS value was determined.

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