New Procedures to Estimate Water Temperatures and Water Depths for Application in Climate–Dengue Modeling

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ABSTRACT Two new approaches have been developed to estimate water temperatures and water depths in containers that commonly are used as breeding sites for mosquitoes, the primary vectors of dengue viruses. These estimates are incorporated in recently developed stochastic simulation models used to describe the daily dynamics of dengue virus transmission in the urban environment. Water temperature estimates are provided through a regression model that includes meteorological variables not previously used; results show that they are significantly better than those used in previous dengue transmission models. Water depth models use a climatic water budget approach which estimates moisture storage within containers. The water depth models are less precise than those developed for water temperature; however, results are superior to those used in previous models. These new approaches should improve estimates of the impact of water conditions on dengue vectors.

KEY WORDS *Aedes aegypti*, water temperature, water depth, stepwise regression, climatic water budget, climate–dengue modeling

A PAIR OF weather-driven stochastic simulation models have been developed to describe the daily dynamics of dengue virus transmission in the urban environment (Focks et al. 1993a, b; 1995). They currently are used worldwide in dengue control programs and for basic epidemiological research (Sota et al. 1992, Gubler and Clark 1995). Because the models are being used more frequently to estimate the consequences of various climate change scenarios on dengue transmission, we have developed new and improved equations to predict water depth and temperature in the habitat of the immature vector from daily weather station data. The simple meteorological inputs for these equations are atmospheric moisture, air temperature, and precipitation.

The entomological model (CIMSiM) is a weather-driven dynamic life table model of container-inhabiting mosquitoes such as *Aedes aegypti* (L.); it provides inputs to the transmission model (DENSiM) (Focks et al. 1993a, b). Daily estimates of adult mosquito survival, gonotrophic development, weight, and emergence from CIMSiM are used to create the biting mosquito population in DENSiM. The survival and emergence values determine the size of the population, whereas the rate of gonotrophic development and female weight influences biting frequency.

Because the vectors of dengue and the viruses themselves are poikilotherms, the models contain a number of temperature-dependent relationships. In addition, because the eggs and aquatic stages of the vectors are influenced by the presence or absence of water in the immature habitat (primarily artificial containers in the domestic environment), the entomological model has routines to predict water temperatures and depths from weather data and information on the types of receptacles making up the larval habitat (Focks et al. 1993a, b). For many of the temperature relationships, including larval development rates and weight of the pupating mosquito, the models use maximum, minimum, or average air temperatures. In addition, estimates of water temperatures in the various types of containers supporting the immatures are required because these help to determine the developmental rates of eggs, larvae, and pupae. The need to estimate adequately water temperature from observed air temperature also is important, because water temperature influences adult size, and adult size correlates with the amount of food reserves available for egg development (Trpis 1972, Rueda et al. 1990). Warm temperatures lead to small adults that require more blood meals to develop an egg batch. This relationship between adult size and temperature is included in CIMSiM, where adult size estimates the number of replete feeds taken per gonotrophic cycle, a factor significantly influencing biting frequency and hence transmission potential.

The performance of CIMSiM and DENSiM depends on accurately predicting container water temperature and depth; however, this was not done adequately in the original models. Therefore, the goal of the current article was to introduce new, more sophisticated pro-

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Table 1. Variables evaluated within the stepwise multiple regression to estimate water temperatures

Variable	Symbol
Max air temp	MaxT (°C)
Min. air temp	MinT (°C)
Max dew point	MaxDPT (°C)
Min. dew point	MinDPT (°C)
Daytime[a] mean cloud cover	DayCC (10th)
Nighttime[b] mean cloud cover	NightCC (10th)
Sun exposure	SunEXP
Compensation for loss of long-wave radiation	Shelter[c]

[a] 0700–1800 hours.
[b] 1900–0600 hours.
[c] For the covered sites, there is compensation for the loss of long-wave radiation.

cedures to estimate both water temperature and depth for use in CIMSiM and DENSiM, as well as other entomological and transmission models. The "climatic water budget" has the capability to estimate water depth in containers by using daily precipitation and air temperature (Mather 1978). A water budget-based model is superior to the original regression model for prediction of water depth, because it is based on the physical mechanisms of the hydrologic cycle and provides estimates of water depth (moisture storage) through a quantitative relationship between water supply (precipitation) and demand (evaporation).

The current article describes new equations designed to predict maximum and minimum water temperatures, and climatic water budget equations for water-filled artificial containers as a function of various meteorological and physical parameters. The new methods are based upon readily available weather station data which facilitate the estimation of water temperatures and water depths. The improved equations will replace the existing ones in CIMSiM for weather and changes in climate.

Materials and Methods

Data Collection. The 3 containers used for data collection were 3.8- and 19.0-liter containers and an automobile tire, all of which represent common breeding sites for *Ae. aegypti* and other container-inhabiting mosquitoes. The 3.8-liter container was 16.5 cm in diameter and 19.5 cm high. The 19.0-liter container had a diameter of 29.0 cm and a height of 35.5 cm. The following different environmental sites were chosen to represent common situations near human populations: (1) an exposed, uncovered location; (2) a screen-enclosed shed; (3) a shaded site under a large tree; and (4) a shed with a roof, but no walls. Container water maximum and minimum temperatures and depths were measured daily for each site at Gainesville, FL, from 2 May to 16 July 1989.

Weather data for Gainesville were available from the NOAA National Climatic Data Center (NCDC) in Asheville, NC. Gainesville is a *first-order weather station,* which records hourly values of air temperature, dew point temperature, cloud cover, and precipitation to predict daily water depths and maximum-minimum temperatures; only maximum-minimum and daily average ambient values (derived from the hourly dataset) were used in the study.

Stepwise Multiple Regression. A stepwise multiple regression procedure was used to estimate maximum and minimum water temperatures within each container at each site from the weather station data (Table 1). Dew point temperature provides a measure of atmospheric humidity; therefore, the lower the dew point temperature, the greater the evaporation and the lower the water temperature within a container. Cloud cover is an estimate of incoming solar radiation, which has obvious effects on water temperature. The loss of long-wave radiation (heat) from the sheltered sites also is an important measure of heat loss. The *shelter variable,* a coefficient based on the level of cover which varies from 0.0 (no shelter) to 1.0 (full shelter), is 0.0 and 0.2 for sites 1 and 2, and 0.1 for sites 3 and 4 respectively, (e.g., for site 2, the loss of long-wave radiation is reduced by 20% because of the extent of cover). The sun exposure variable modifies water temperatures and varies with degree of shelter, which is 1.0, 0.0, 0.1, and 0.1 for sites 1–4, respectively. Therefore, for site 1, 100% of sunlight reaches the containers, whereas for site 2 (within the screen-enclosed shed), virtually no direct solar radiation impinges upon the containers.

Complete step-up multiple linear regressions were run, which included regression diagnostics such as

Table 2. Stepwise regressions for water temperatures

Step	Variable[a]	Coefficient	Model R^2	SE	F
		Max water temp, °C			
	Intercept	9.1588	—	1.70	29.05***
1	SunEXP	8.0821	0.5812	0.31	692.95***
2	MaxT (°C)	0.4590	0.7266	0.07	49.18
3	MinDPT (°C)	0.1951	0.7484	0.04	26.01
		Min. water temp, °C			
	Intercept	3.4325	—	0.67	26.58
1	MinT (°C)	0.6009	0.7500	0.06	98.58
2	Shelter	9.2105	0.7896	1.20	59.29
3	MaxDPT (°C)	0.2674	0.7996	0.07	15.06

***, $P < 0.001$.
[a] For explanation of symbols, see Table 1.

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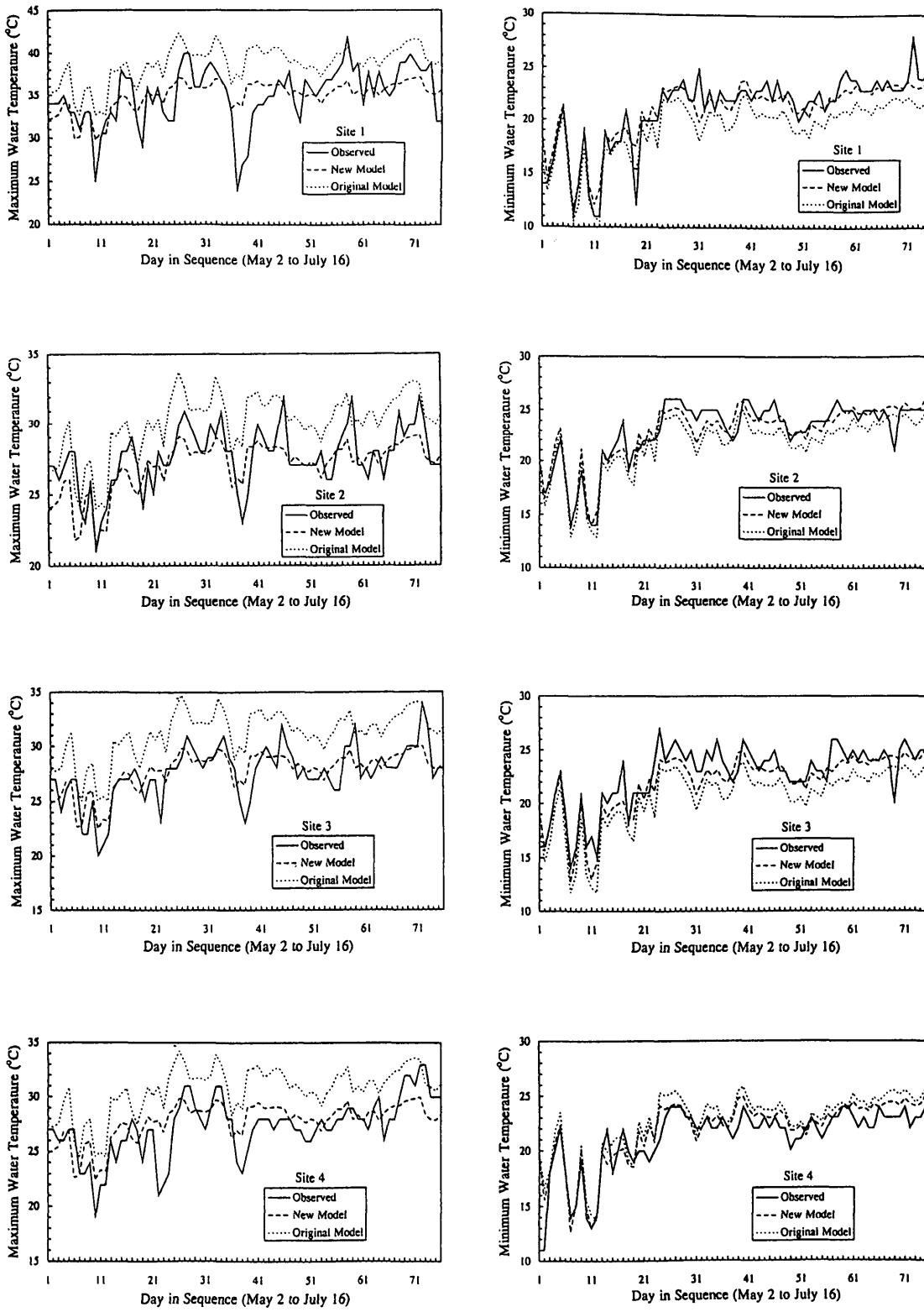

Fig. 1. New and original models—predicted versus observed maximum and minimum water temperatures.

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residuals plots and variance inflation factors (VIF) (Draper and Smith 1981, SAS Institute, 1994 SAS Institute 1994). A high VIF indicates that ≥2 collinear independent variables are included in the model. When this occurs, the collinear variable with the lower partial correlation is omitted. The selected water temperature regression model (1 for maximum water temperature; 1 for minimum water temperature) must meet the following criteria: (1) all included independent variables must be significant at the ≥0.05 level, (2) the VIF for all independent variables must be ≤2.00 (SAS Institute 1994); and (3) the residuals plots must indicate randomly distributed residuals.

Climatic Water Budget. According to Mather (1978), the climatic water budget is a monthly, weekly, or daily comparison of water supply (precipitation) and climatic demands for water (evapotranspiration). In our study, water depths were predicted for containers assuming that evaporation was the only climatic demand for water. Within the Thornthwaite-Mather water budget approach used here (Mather 1978), several parameters must be initialized, including latitude of the study site, water depth in a container just before the beginning of calculations (initial water volume of the container), water-holding capacity of the container (height of the container), and an annual heat index. The heat index represents the annual average thermal condition and is determined from the sum of the 12 monthly heat index values, which are an empirical function of mean monthly temperature (Thornthwaite 1948).

After these initial parameters are set, the WATBUG water budget program calculates daily values of *potential evaporation* (PE), defined as the water loss from a water surface that never suffers from a lack of water, *actual evaporation* (AE), *moisture storage* (STO), *water deficit* (DEF), and *water surplus* (SUR) (for details, see Mather 1978 and Willmott 1977). In this study, a daily water budget was used, which permits day-by-day estimates of all the water budget variables. We are most interested in moisture storage (STO), because it represents the amount of water within a container for every day during the study period.

Water depths for the 3 different containers (3.8 and 19.0 liter, tire) were modeled using the Thornthwaite-Mather water budget (Mather 1978). The daily mean air temperature, precipitation, and the initial parameters were input into the water budget model. Output was the daily water depth of the container (STO). The observation on 2 May 1989 of actual water depth was used as the initial water volume for each container. For the protected sites, such as under a tree and in the screen-enclosed shed, the daily mean air temperature and precipitation totals were modified by local influences. Observations indicated that daily mean air temperatures are ≈2°C cooler in these protected areas, and temperatures from the weather station were adjusted accordingly.

Precipitation differentials were somewhat more varied; obviously less precipitation reaches the containers in the enclosed shed, but observations indicate that considerably more precipitation is available to

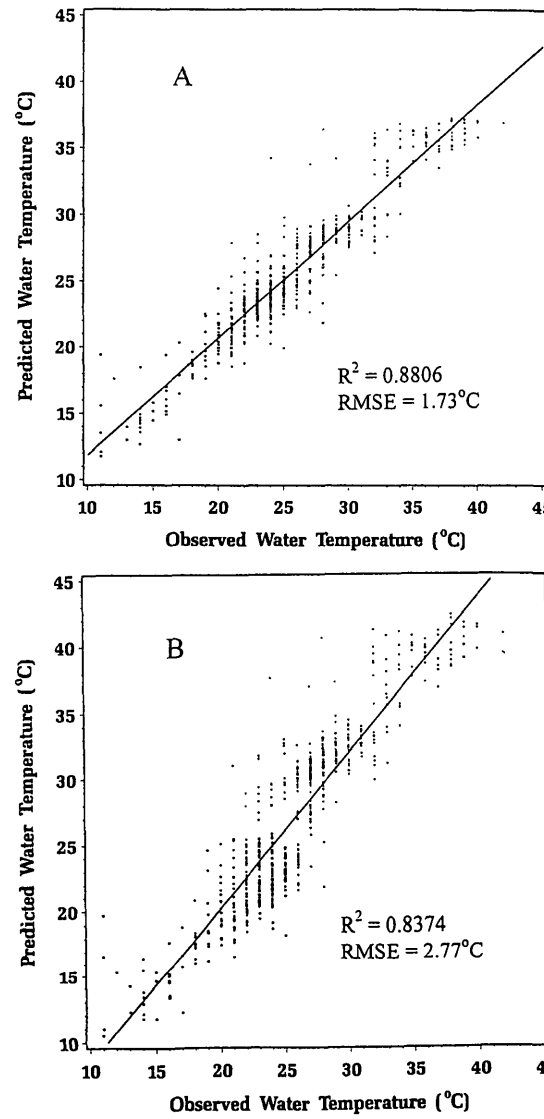

Fig. 2. Model evaluation of maximum and minimum water temperatures. (A) New model. (B) Original model.

containers under the tree, primarily because of stem and trunk flow. Although precipitation was not recorded for the different sites, the alteration of water depth in each of the containers showed that water depth decreased throughout the study period at site 2 and increases after early June at site 3. Fluctuations in water depth were particularly large at site 3, but the gradual seasonal increase is indicative of more precipitation here than at site 2. From these water depth values, we estimated that the daily rainfall amount from the weather station should be decreased 20% for site 2 and increased 30% for site 3. As site 1 was uncovered, no adjustments in temperature or precipitation were necessary. In addition, no adjustments were made for site 4 because it appeared that precipitation penetrated almost unimpeded, possibly be-

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cause of the lack of walls. The best models at site 4 were those with no temperature and precipitation adjustments.

Results and Discussion

Water Temperatures. The data from all sites were combined, and 304 observations from 2 May through 16 July 1989 were used in the regression analysis. If the data are pooled, one regression equation can be developed for all sites, which is consistent with the original model (Focks et al. 1993a). In addition, the impacts of sun exposure and shelter can be evaluated, because they did not vary within sites.

The stepwise multiple regression results for daily maximum and minimum water temperatures are shown in Table 2. The model coefficient of determinations (R^2) are strong and explain about 75% of the variance in maximum water temperature and about 80% of the variance in minimum water temperature. The derived equations are as follows:

$$MaxT_w = 9.1588 + 8.0821SunExp + 0.4590MaxT + 0.1951\ MinDPT \quad [1]$$

$$MinT_w = 3.4325 + 0.6009MinT + 9.2105Shelter + 0.2674\ MaxDPT, \quad [2]$$

where $MaxT_w$ and $MinT_w$ are the predicted maximum and minimum water temperatures (°C).

The results provide some interesting insights involving those variables most influential on water temperature. Maximum air temperature was statistically significant and important in the maximum water temperature regression, and accounted for ≈15% of the variance. Minimum air temperature obviously was most important in the minimum water temperature regression and explained 75% of the total variance. Available solar radiation was the most important determinant in the maximum water temperature model, accounting for ≈58% of the variance. Shelter also was statistically significant in the minimum water temperature regression; shelter reduced the escape of energy at night, keeping minimum water temperatures comparatively high. Solar radiation variables dropped out of the minimum water temperature model because only long-wave radiation was important during the night. Atmospheric moisture content (as expressed by the dew point) also was significant in the regression models. High dew point temperatures raised the specific heat of the atmosphere and lessened energy loss from the water.

The regression equations appeared to be better predictors of maximum and minimum water temperatures than the original models developed by Focks et al. (1993a) (Fig. 1). The original models usually overestimated maximum water temperature and underestimated minimum water temperature; this clearly is not the case with the new models. The addition of the shelter variable no doubt has assisted in refining the estimates developed using the new algorithms for minimum water temperature. In addition, the dew point variables are included within the new algorithms, and they permit an estimate of evaporative cooling of the water, which may occur on relatively dry days. Both variables were not included within the algorithms used by Focks et al. (1993a).

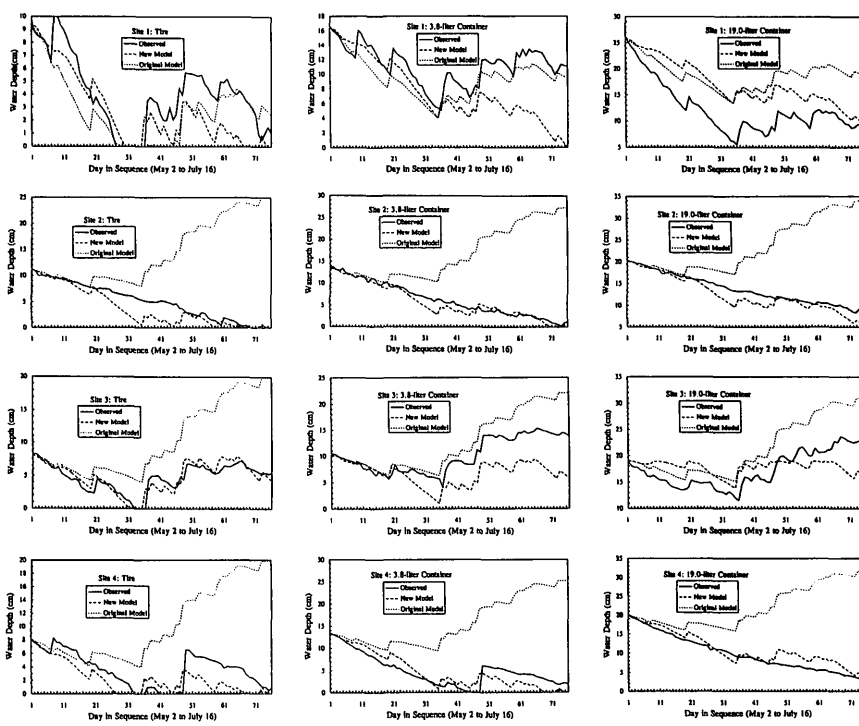

Fig. 3. New and original models—predicted versus observed water depths.

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Table 3. Root mean squared error of the prediction for water temperature

Model	Max water temp, °C				Min. water temp, °C			
	Site 1	Site 2	Site 3	Site 4	Site 1	Site 2	Site 3	Site 4
This Study	3.66	2.56	2.81	2.70	1.20	1.05	1.30	1.53
Focks et al. (1993a)	4.61	3.00	3.96	3.94	2.21	1.71	2.48	2.07

To provide a statistical evaluation of both new and original models, a comparison between predicted and measured maximum and minimum water temperatures for all sites combined was developed (Fig. 2). The results presented in these figures were derived by using equations 1 and 2 for the new model as well as equations in Focks et al. (1993a) for the original model. The new model R^2 (0.88) is greater and the root mean squared error (RMSE) of prediction is much smaller (1.73°C) in the new model than in the original (0.84 and 2.77°C, respectively). An evaluation by each site confirmed that the RMSE of prediction for both maximum and minimum temperatures was considerably less using the new model (Table 3). Results were particularly good for the new minimum temperature model.

Water Depths. Fig. 3 compares water depth estimates within the 3 containers using our new water budget model and the original model from Focks et al. (1993a). The new water depth models were less precise than those developed for water temperature, but were notably better than those developed by Focks et al. (1993a). The original model performed better for 3.8-liter containers at sites 1 and 3; however, for the remaining containers, the differential between actual and modeled water depth increased as the study period progressed using the water depth models found in Focks et al. (1993a). With the original model, there was gross overprediction of water depths by the end of the study for almost all containers because most did not receive significant precipitation due to their protected nature.

The new water budget-based estimates had a tendency to underpredict water depth. In some cases, this underprediction is obvious, especially for the smaller containers at the more exposed sites (e.g., the 3.8-liter container at site 1). Results using the water budget-based approach were very good for the 19.0-liter container, especially in the protected sites. The tire estimates also were improved, and the water budget models properly estimated periods when the tire dried out completely.

The model evaluation for water depth (Fig. 4) indicated that the predictive ability of the new model was much better than the original one. The new model explained >76% of the variance in the total dataset composed of all sites, and the RMSE was <1/3 of the original model. When discriminating by site, the RSME in most cases was lower for the new model, with the exception of the 3.8-liter container for sites 1 and 3 (Table 4). Results were particularly improved for sites 2 and 4 for all containers.

There remains a need to improve some of the water budget-based water depth models. However, even in their current form, they represent an attractive alternative to the models originally used by Focks et al. (1993a). Because these models are based on water budget parameters, they represent a more accurate simulation of the hydrologic cycle within the containers than did previous models which relied more heavily on raw meteorological data. It is expected that the application of these new procedures for estimating

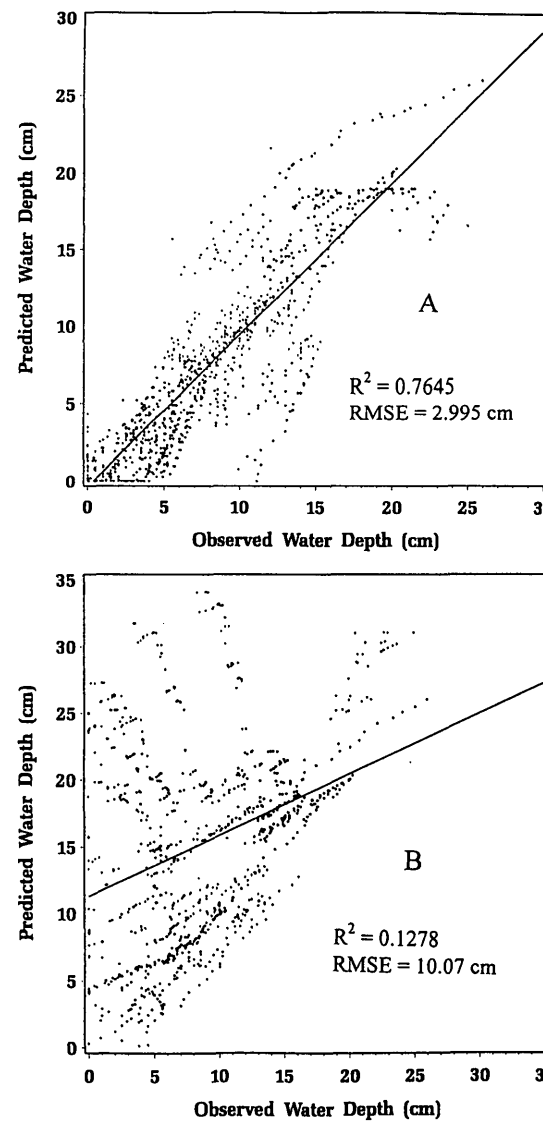

Fig. 4. Model evaluation of water depths. (A) New model. (B) Original model.

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Table 4. Root mean squared error of the prediction for water depth (cm)

Site no.	Container	This study	Focks et al. (1993a)
1	Tire	2.10	2.25
	3.8 liter	5.04	2.16
	19.0 liter	5.41	7.20
2	Tire	2.00	13.26
	3.8 liter	1.09	14.20
	19.0 liter	1.67	13.47
3	Tire	1.02	7.38
	3.8 liter	4.42	3.64
	19.0 liter	3.38	4.92
4	Tire	2.18	9.25
	3.8 liter	1.89	13.15
	19.0 liter	1.82	15.70

water temperature and depth within existing dengue transmission models will enhance both retrospective and prospective evaluations of the spread of this disease.

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References Cited

Draper, N., and H. Smith. 1981. Applied regression analysis, 2nd ed. Wiley, New York.

Focks, D. A., D. G. Haile, E. Daniels, and G. A. Mount. 1993a. Dynamic life table model for *Aedes aegypti* (L.) (Diptera: Culicidae). Analysis of the literature and model development. J. Med. Entomol. 30: 1003–1017.

1993b. Dynamic life table model for *Aedes aegypti* (L.) (Diptera: Culicidae). Simulation results and validation. J. Med. Entomol. 30: 1018–1028.

Focks, D. A., E. Daniels, D. G. Haile, and J. E. Keesling. 1995. A simulation model of the epidemiology of urban dengue fever: literature analysis, model development, preliminary validation, and samples of simulation results. Am. J. Trop. Med. Hyg. 53: 489–506.

Gubler, D. J., and G. G. Clark. 1995. Dengue/dengue hemorrhagic fever: the emergence of a global health problem. Dispatches Emerging Infect. Dis. 1: 55–57.

Mather, J.R. 1978. The climatic water budget in environmental analysis. Heath, Lexington, MA.

Rueda, L. K., K. J. Patel, R. C. Axtell, and R. E. Stinner. 1990. Temperature-dependent development and survival rates of *Culex quinquefasciatus* and *Aedes aegypti* (Diptera: Culicidae). J. Med. Entomol. 27: 892–898.

SAS Institute. 1994. SAS/STAT user's guide, version 6, 4th ed. SAS Institute, Cary, NC.

Sota, T., M. Mogi, and E. Hayamizu. 1992. Seasonal distribution and habitat selection by *Aedes albopictus* and *Aedes riversi* (Diptera: Culicidae) in Northern Kyushu, Japan. J. Med. Entomol. 29: 296–304.

Thornthwaite, C. W. 1948. An approach toward a rational classification of climate. Geogr. Rev. 38: 55–94.

Trpis, M. 1972. Seasonal changes in the larval populations of *Aedes aegypti* in two biotopes in Dar es Salaam, Tanzania. Bull. W.H.O. 47: 245–255.

Willmott, C. J. 1977. WATBUG: a FORTRAN IV algorithm for calculating the climatic water budget. Publications in Climatology 30(2). C. W. Thornthwaite Associates, Laboratory of Climatology, Elmer, NJ.

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