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*GeoHealth*

Supporting Information for

**Investigating the Impact of Irrigation on Malaria Larval Habitats and Transmission Using a Hydrology-based Model**

Ai-Ling Jiang<sup>1</sup>, Ming-Chieh Lee<sup>2</sup>, Prashanth Selvaraj<sup>3</sup>, Teshome Degefa<sup>4,5</sup>, Hallelujah Getachew<sup>4,5,6</sup>, Hailu Merga<sup>7</sup>, Delenasaw Yewhalaw<sup>4,5</sup>, Guiyun Yan<sup>2</sup>, Kuolin Hsu<sup>1</sup>

<sup>1</sup> Center for Hydrometeorology and Remote Sensing, Department of Civil and Environmental Engineering, University of California Irvine, Irvine, CA, USA

<sup>2</sup> Department of Population Health and Disease Prevention, School of Public Health, Susan and Henry Samueli College of Health Sciences, University of California Irvine, Irvine, CA, USA

<sup>3</sup> Institute for Disease Modeling, Bill and Melinda Gates Foundation, Seattle, WA, USA

<sup>4</sup> School of Medical Laboratory Sciences, Institute of Health, Jimma University, Jimma, Ethiopia

<sup>5</sup> Tropical and Infectious Diseases Research Center (TIDRC), Jimma University, Jimma, Ethiopia

<sup>6</sup> Department of Medical Laboratory Technology, Arbaminch College of Health Sciences, Arba Minch, Ethiopia

<sup>7</sup> Department of Epidemiology, Institute of Health, Jimma University, Jimma, Ethiopia

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**Introduction**

This file contains additional information on data collection, model development, calibration and simulation results.

## 28 **Text S1. Larval density estimation**

29 In the study area, the surveyed larval habitats include drainage ditch, river edge/reservoir  
30 shoreline, swamp/marsh, rice puddle, animal footprint, tire track/road puddle, man-made pond,  
31 natural pond/rain pool, rock pool, water container, irrigation canal, and brick pit. The larval  
32 habitats were classified as temporary, semi-permanent, or permanent based on their natural  
33 characteristics. Since larval density can be significantly different in the dry and rainy seasons  
34 (Hinne et al., 2021; Kweka et al., 2012) and the timing and duration of the survey periods were  
35 inconsistent, we sorted the measured larval densities from the 769 sample points (Figure 1) into  
36 the dry season (January to April; November to December) and the rainy season (May to  
37 October). We then calculated the average larval density for each season as shown in Figure S4.

38 In the surveyed area, the larval density for temporary habitats was higher in the rainy  
39 season than in the dry season during which the habitats are less stable. On the other hand, the  
40 larval densities for semi-permanent and permanent habitats were higher in the dry season. Most  
41 of the semi-permanent and permanent habitats were associated with river edges and swamps,  
42 whereby the larvae are prone to flushing in the rainy season. Finally, the larval density in Table 1  
43 was calculated based on the average dry season and rainy season densities.

## 44 **Text S2. Irrigation schedule design**

45 Figure S6 shows the monthly irrigation schedule obtained from the Arjo-Didessa Sugar  
46 Factory, which is tailored to the sugarcane planting cycle.

47 To model irrigation in ParFlow-CLM, the irrigation interval and rate are required user  
48 inputs. A report provided by the factory recommended 8-12 days for the design of the local  
49 irrigation system, so we set the irrigation interval as 10 days.

50 To determine the irrigation rate, we first calculated the irrigation depth, defined as the  
51 amount of water that needs to be applied when the soil water content is depleted to the wilting  
52 point. The irrigation depth ( $IrrD$ ) was calculated as

$$53 \quad IrrD = (FC - WP) \times Depth_{soil}, \quad (S1)$$

54 where  $FC$  is the field capacity,  $WP$  is the permanent wilting point and  $Depth_{soil}$  is the soil  
55 depth.

56 The study area is characterized by clay and clay loam with low permeability. Based on  
57 resources by the Northeast Region Certified Crop Advisor  
58 (<https://nrcca.cals.cornell.edu/soil/CA2/CA0212.1-3.php>), the field capacity volumetric soil  
59 moisture content of clay was set as 50%, and the wilting point volumetric soil moisture content  
60 was set as 15%. A soil depth of 2 m was assumed. Using Equation (S1), an irrigation depth of  
61 700 mm was obtained.

62 We configured the irrigation to be applied when 50% of the irrigation depth was  
63 depleted; hence, the actual irrigation depth to be applied over the 10-day irrigation interval was  
64 350 mm. Adopting an intermittent irrigation strategy, we set the irrigation to be applied for 22  
65 hours a day over 3 days within the 10-day cycle. The irrigation rate was then calculated to be 5.3  
66 mm/hour.

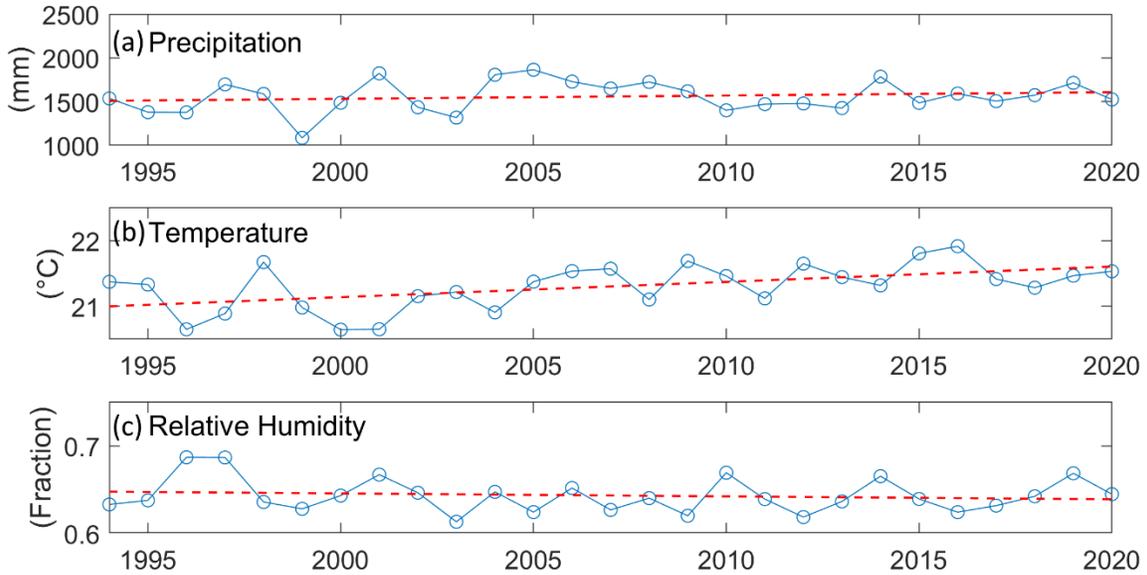
67 **Text S3. Model calibration**

68 At each grid cell, ponding is assumed to occur if the soil saturation exceeds the  
69 threshold,  $\theta$ . Therefore, the threshold was calibrated to ensure that the model will predict the  
70 occurrence of ponding at locations in line with the field-surveyed larval habitats for soil  
71 saturation above  $\theta$ . The value for  $\theta$  was obtained based on a sensitivity analysis by altering the  
72 threshold and noting the corresponding change in the probability of detection (*POD*). The *POD*  
73 determines if the model can predict an aquatic habitat successfully and can be calculated based  
74 on the ratio of the number of successful predictions or hits,  $H$ , to the total number of samples,  $S$ :

75 
$$POD = H/S, \quad (S2)$$

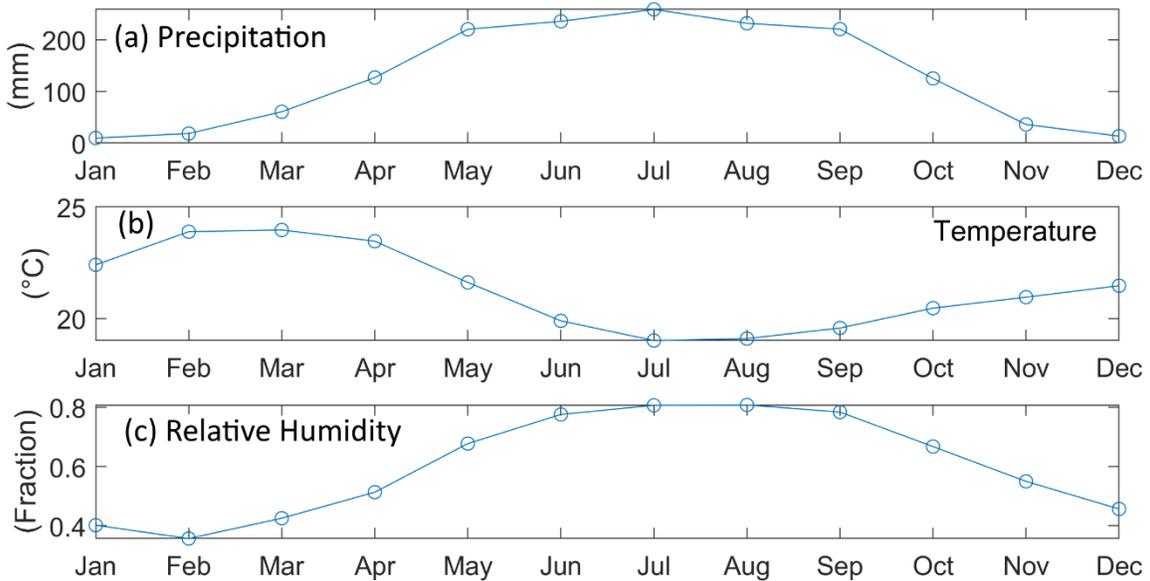
76 Figure S8 shows the results of the sensitivity analysis. Generally, the *POD* curve is higher  
77 for the simulation excluding dry season. This is because irrigation was only approximated by a  
78 simplified scheme in the dry season and may not reflect the localized irrigation dynamics. As the  
79 threshold was lowered, *POD* increased because ponding occurred across a larger area in the  
80 model. The influence of topography on the ponding was weakened, and the soil type became  
81 the dominant factor. On the other hand, when the threshold was increased, less ponding was  
82 predicted, resulting in a lower *POD* but the topographic variability was better represented.  
83 Therefore, we selected a threshold of 0.75 for a reasonable *POD* of 0.66 (excluding dry season)  
84 without obscuring topographic variability.

85 In EMOD, we calibrated 15 key parameters identified from a preliminary sensitivity  
86 analysis, and Table S3 presents the calibrated values. Using the calibrated parameters, we  
87 compared the simulated prevalence rate against field data for January 2018 and October 2018  
88 (Figure S9). The results are within the same order of magnitude. In addition, we compared the  
89 simulated monthly number of clinical cases with the recorded malaria cases from April 2018 to  
90 May 2020 (Figure S10). Apart from the two peaks missed in October 2018 and November 2019,  
91 the simulated malaria cases compare reasonably well with observation in terms of magnitude  
92 and pattern. As the clinical malaria cases were sourced from major hospitals within the study  
93 area, the two peaks in recorded cases could be anomalous due to an influx of patients from  
94 outside seeking treatment at the hospitals. Overall, the model shows a good agreement with the  
95 field observation.



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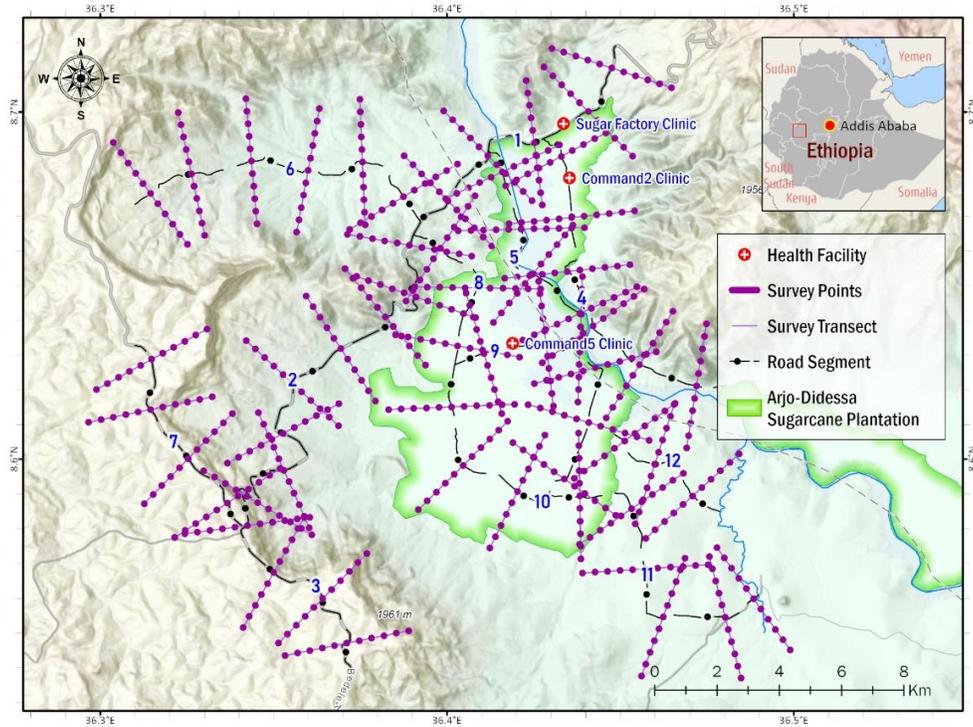
97 **Figure S1.** Annual climate data from PERSIANN-CCS-CDR and ERA5 for the study area. (a) total  
 98 precipitation, (b) average temperature and (c) average relative humidity. The red dashed line  
 99 represents the linear trendline in each subplot.



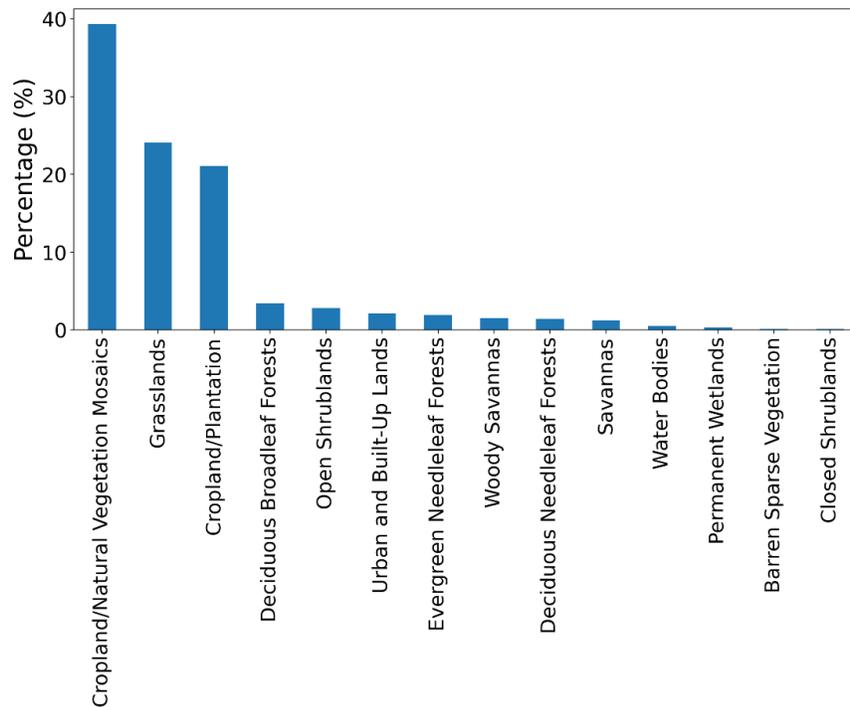
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101 **Figure S2.** Monthly climate data (averaged from 1994 to 2020) derived from PERSIANN-CCS-  
 102 CDR and ERA5 climate data for the study area. (a) total precipitation, (b) average temperature,  
 103 and (c) average relative humidity.

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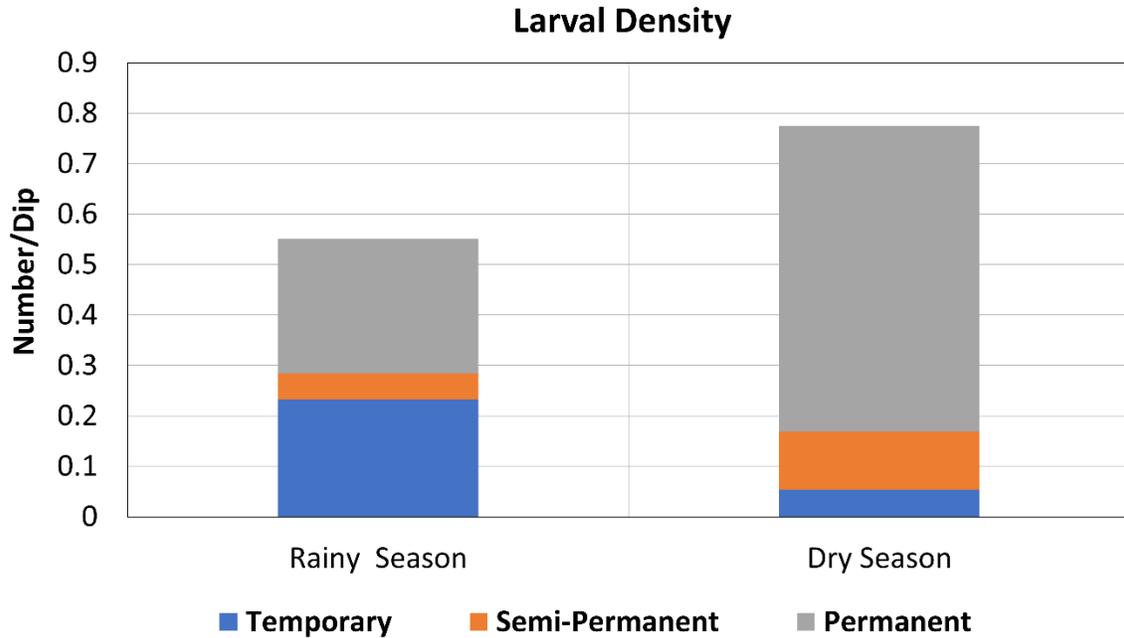


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106 **Figure S3.** Land use survey locations.



107  
108 **Figure S4.** Percentage distribution of International Geosphere-Biosphere Programme type from  
109 land use survey.

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111  
 112 **Figure S5.** Average larval densities for temporary, semi-permanent, and permanent habitats  
 113 during rainy and dry seasons from field survey.

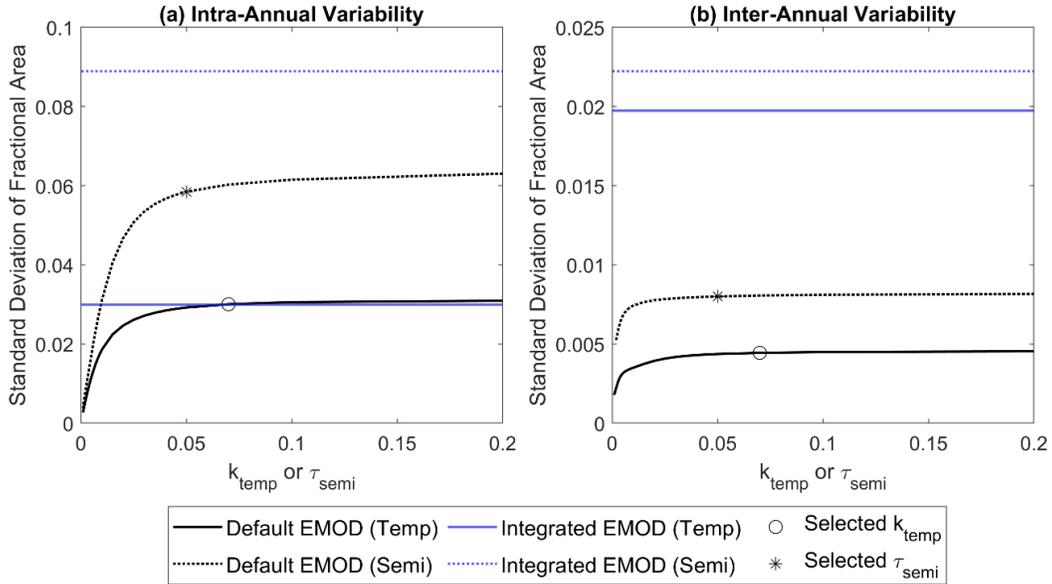
(a)	1 <sup>st</sup> Year (Virgin Planting)												2 <sup>nd</sup> Year (Virgin Planting)												1 <sup>st</sup> Ratoon				
	Mn	1	2	3	4	5	6	7	8	9	10	11	12	1	2	3	4	5	6	7	8	9	10	11	12	1	2	3	4
Sym.	MA	H	H	LW	P	P	P	P	RF	RF	IR	IR	IR	IR	IR	IR	RF	MA	MA	MA	H	IR	IR						

(b)	1 <sup>st</sup> Ratoon												2 <sup>nd</sup> Ratoon												Virgin Planting				
	Mn	1	2	3	4	5	6	7	8	9	10	11	12	1	2	3	4	5	6	7	8	9	10	11	12	1	2	3	4
Sym.	MA	H	IR	IR	RF	RF	RF	RF	RF	RF	MA	MA	MA	H	IR	IR	RF	MA	MA	MA	H	H	LW						

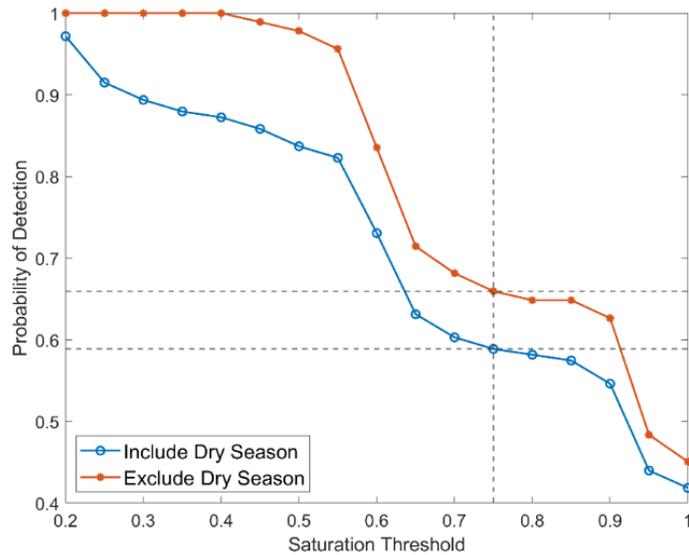
114  
 115 **Figure S6.** Arjo-Didessa Sugar Factory sugarcane plantation irrigation schedule. A typical sugar  
 116 planting schedule includes (a) a 2-year cycle for virgin planting and (b) a 1-year cycle for the  
 117 following 2 ratoons. MA: Maturity/water drain; H: Harvesting; LW: Land work; P: Planting; RF:  
 118 Rainfed; IR: Irrigation.

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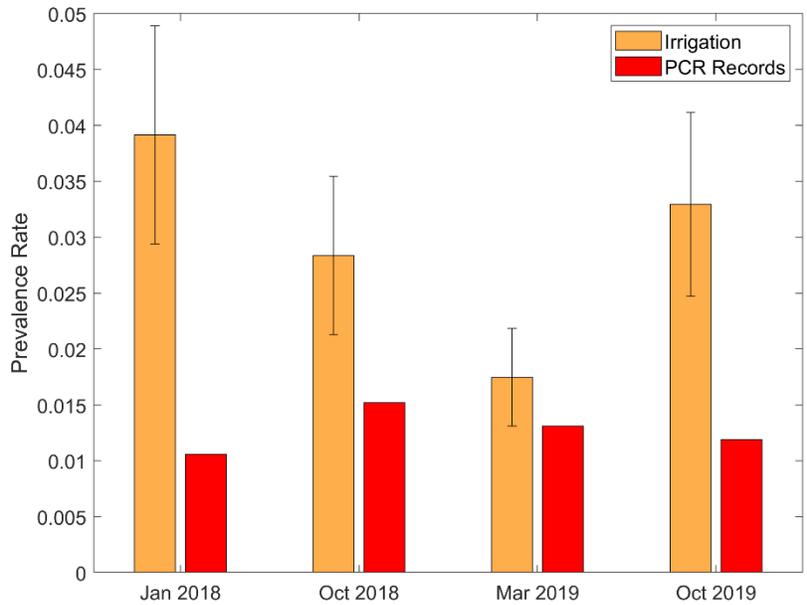
121 **Figure S7.** Adjustment of decay factors for temporary and semi-permanent habitats in default  
 122 EMOD function. The objective was to match the (a) intra-annual variability and (b) inter-annual  
 123 variability of the habitats from the hydrologic model as closely as possible. The decay factor of  
 124 semi-permanent habitat also had to be smaller than that of temporary habitat. Intra-annual  
 125 variability was measured in terms of the standard deviation of the 20-year average habitat area  
 126 for each day of the year. Inter-annual variability was characterized by the standard deviation of  
 127 the annual average habitat area for each year.



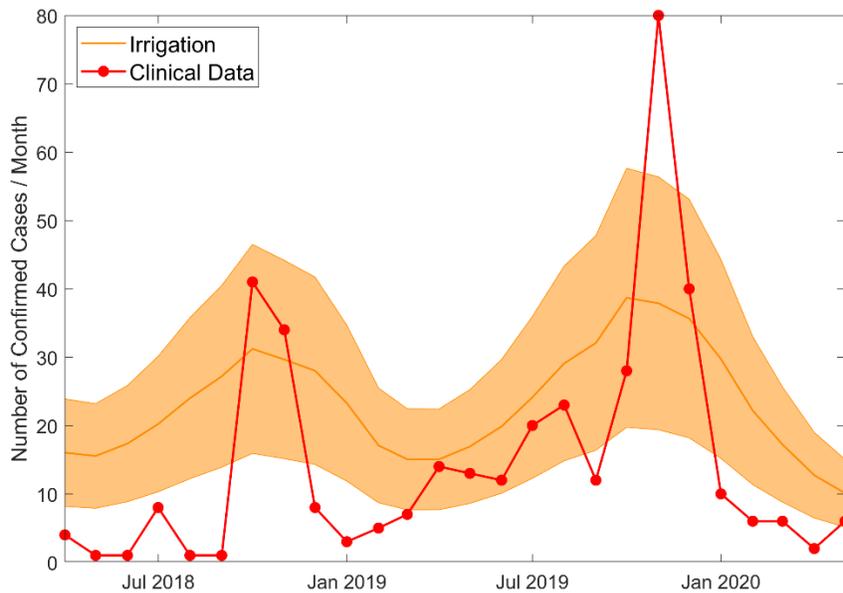
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129 **Figure S8.** Sensitivity analysis of the probability of detection to saturation threshold. The  
 130 probability of detection determines if the model can predict an aquatic habitat successfully and  
 131 can be calculated based on the ratio of successful predictions to the total number of  
 132 observations. The dotted vertical line corresponds to the selected threshold of 0.75, which

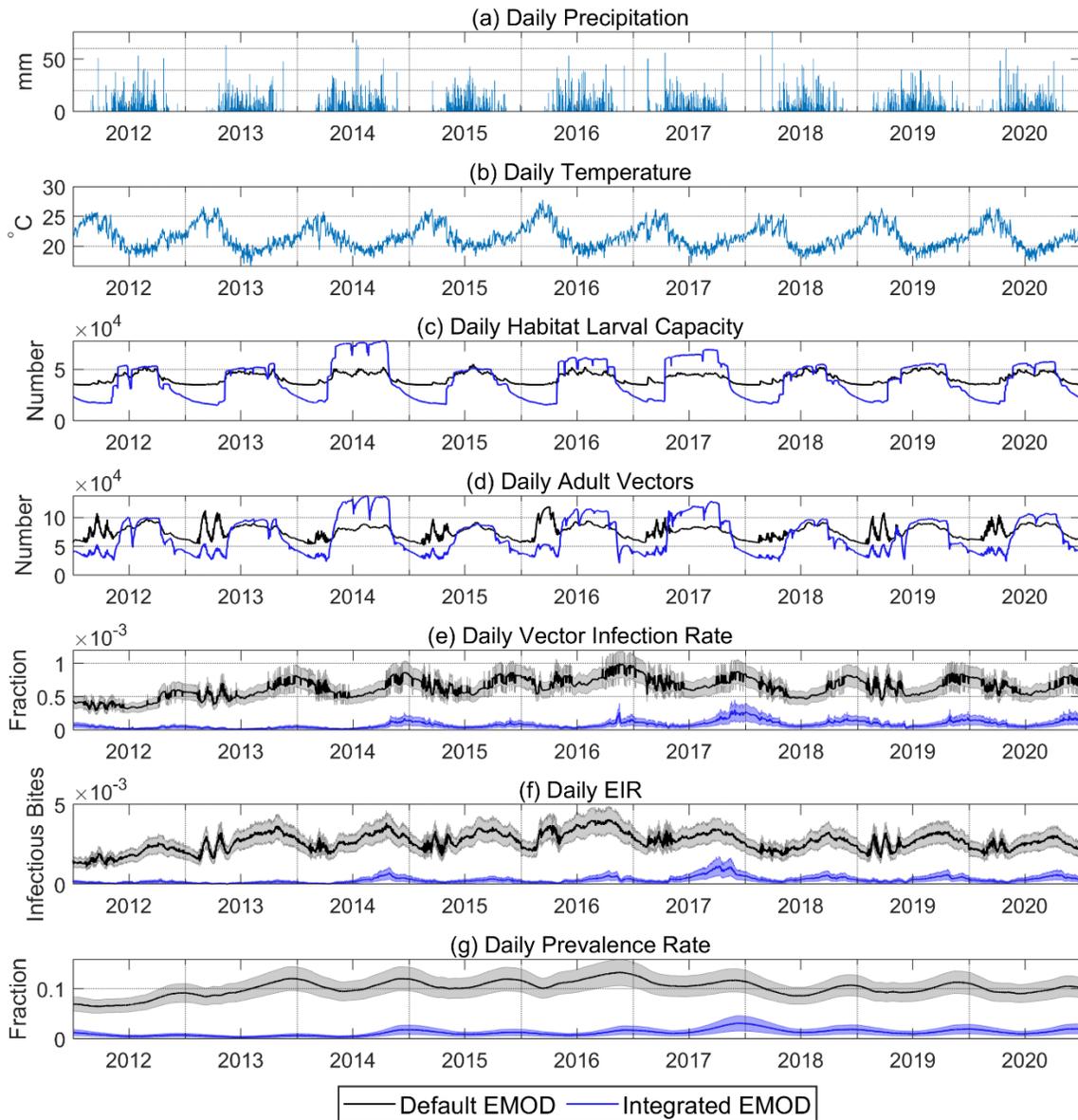
133 results in a reasonable POD of 0.66 excluding dry season and a POD of 0.59 including dry  
 134 season.  
 135



136  
 137 **Figure S9.** Comparison of simulated monthly average prevalence rate in *Irrigation* and  
 138 measured prevalence diagnosed by Polymerase Chain Reaction (PCR). The whisker on the bar  
 139 plot represents one standard error.



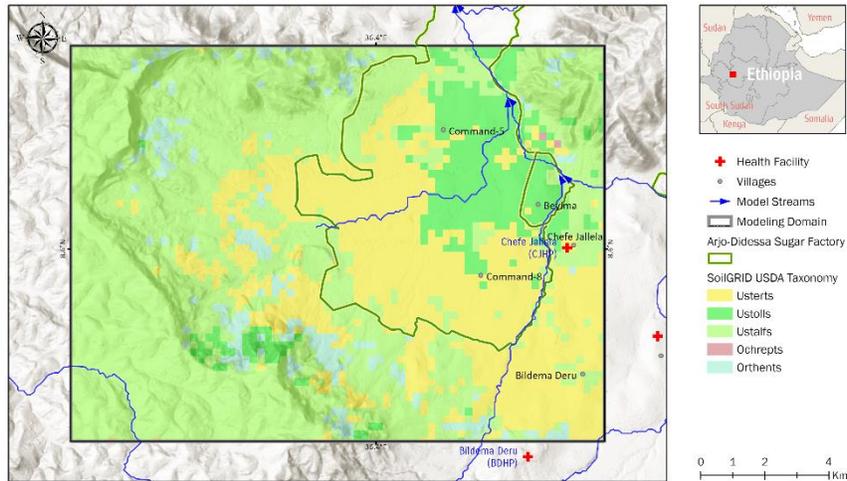
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 141 **Figure S10.** Comparison of simulated monthly confirmed cases in *Irrigation* and clinical data.  
 142 The orange band indicates the 95% confidence interval.



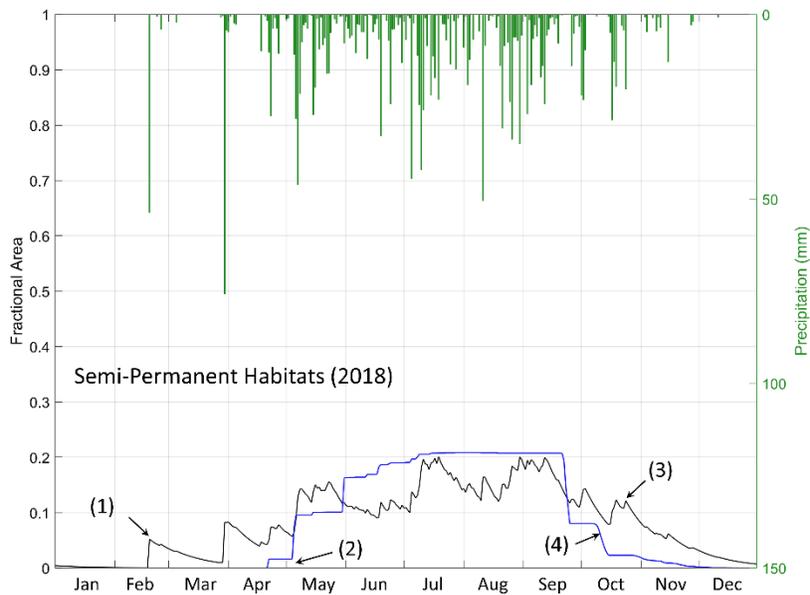
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144 **Figure S11.** Time series of daily climate data and comparison of simulated daily malaria  
 145 transmission results between *Default EMOD* and *Integrated EMOD*. Climate data include (a)  
 146 precipitation and (b) temperature. Malaria transmission results include (c) habitat larval capacity,  
 147 (d) adult vector abundance, (e) adult vector infection rate, (f) entomological inoculation rate and  
 148 (g) parasite prevalence rate. The simulation was performed for 20 years from 2000 to 2020, but  
 149 here we only show the results from 2010 to 2020 for simplicity.

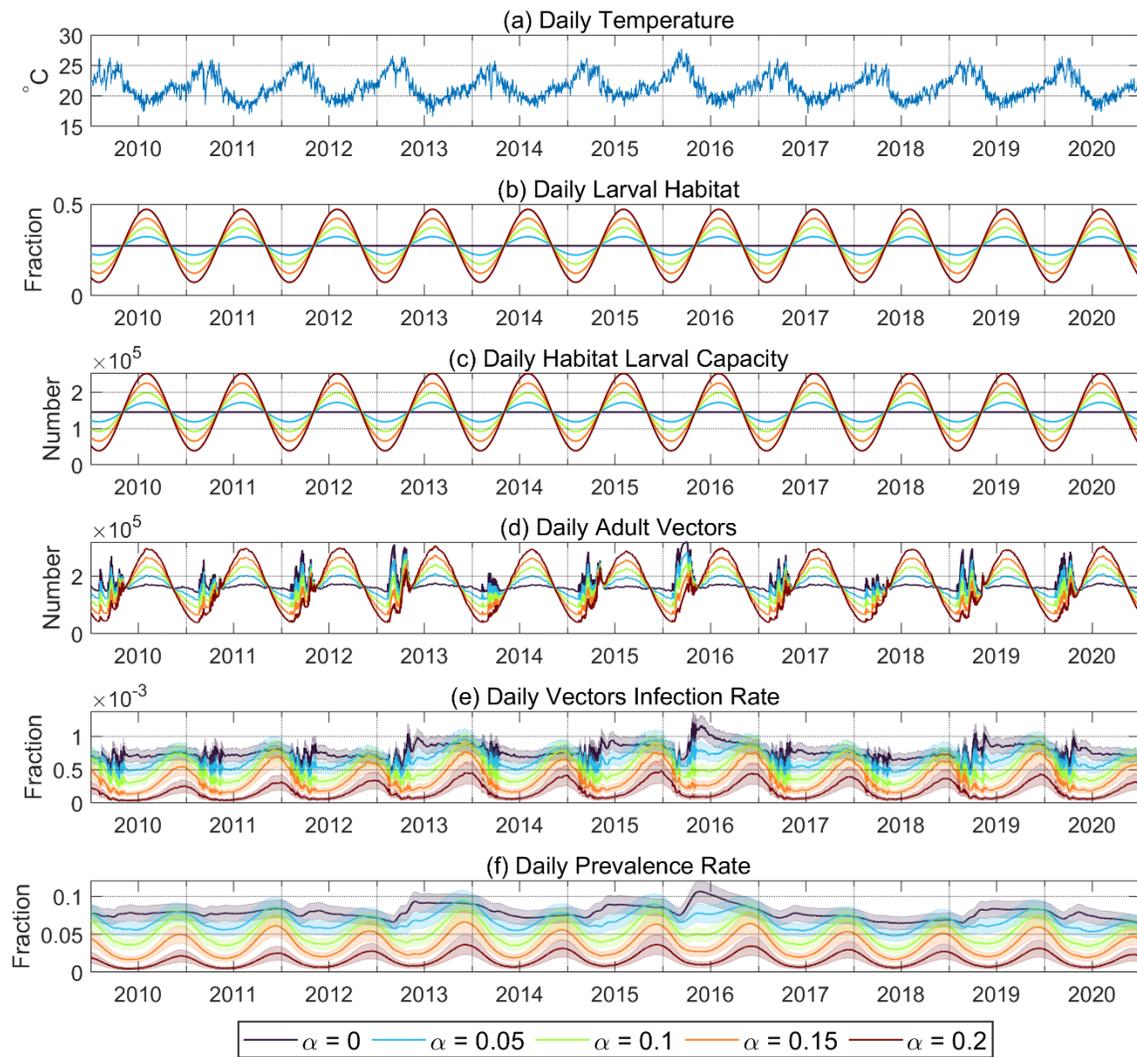
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 152 **Figure S12.** The distribution of the top two-meter soil types in USDA soil taxonomy from  
 153 SoilGrids250m TAXOUSA dataset. Most soil types in this area are characterized as clay or clay  
 154 loam with low permeability ranging from 0.0015 to 0.015 m/h.



156  
 157 **Figure S13.** Comparison of simulated semi-permanent habitats between *Default EMOD* (black  
 158 line) and *Integrated EMOD* (blue line) in 2018. Earlier rising limb in *Default EMOD*: (1) no  
 159 infiltration, new ponds created instantaneously by rainfall; (2) ponds formed sometime after  
 160 rainfall when soil saturation exceeded the threshold. Delayed falling limb in *Default EMOD*: (3)  
 161 habitat area continued to increase with rainfall; (4) pond drained/dried up and soil became  
 162 unsaturated after a period without rainfall, new rainfall insufficient to create ponding as soil  
 163 saturation remained below threshold.



165

166 **Figure S14.** Simulation results from sensitivity analysis of malaria transmission to different  
 167 amplitudes of larval habitat seasonality,  $\alpha$ . Time series include (a) daily temperature, (b)  
 168 synthetic sinusoidal larval habitat, (c) habitat larval capacity, (d) adult vector abundance, (e) adult  
 169 vector infection rate and (f) parasite prevalence rate.

170

171 **Table S1.** Input data for ParFlow-CLM and EMOD.

Variable	Resolution	Latency	Source
<b>Topography</b>	5-meter	-	ALOS WORLD 3D Topographic Data (Takaku et al., 2016; Takaku and Tadono, 2017)
<b>Precipitation</b>	0.04°×0.04°, 3-hourly	~1 hour	Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks -Cloud Classification System- Climate Data Record (PERSIANN-CCS-CDR) (Sadeghi et al., 2021)
<b>Surface Solar Radiation Downwards</b>	0.25°×0.25°, 1-hourly	5 days	The Fifth Generation European Centre for Medium-Range Weather Forecasts Reanalysis (ERA5) (Hersbach et al., 2020, 2018)
<b>Surface Thermal Radiation Downwards</b>	0.25°×0.25°, 1-hourly	5 days	ERA5
<b>Air Temperature</b> (2m above ground surface)	0.25°×0.25°, 1-hourly	5 days	ERA5
<b>Skin Temperature</b>	0.25°×0.25°, 1-hourly	5 days	ERA5
<b>Surface Pressure</b>	0.25°×0.25°, 1-hourly	5 days	ERA5
<b>Water-vapor specific humidity</b>	0.25°×0.25°, 1-hourly	5 days	ERA5
<b>North-to-South Component of Wind Speed</b> (10m above ground surface)	0.25°×0.25°, 1-hourly	5 days	ERA5
<b>East-to-West Component of Wind Speed</b> (10m above ground surface)	0.25°×0.25°, 1-hourly	5 days	ERA5
<b>Land Use (2000)</b>	30-meter	-	Global Land Cover Mapping Project (GlobeLand30) (Chen et al., 2015)
<b>Land Use (2010)</b>	30-meter	-	GlobeLand30
<b>Land Use (2020)</b>	30-meter	-	GlobeLand30

<b>Soil Type</b>	250-meter	-	SoilGrids250m, TAXOUSA (Hengl et al., 2017)
<b>Depth to Bedrock</b>	250-meter	-	SoilGrids250m, BDRICM (Hengl et al., 2017)
<b>Near Surface Permeability (&lt; 100 m)</b>	Regional Scale	-	GLobal HYdrogeology MaPS 2.0 (GLHYMPS, 2.0) (Gleeson et al., 2014)

172 **Table S2.** Field data for ParFlow-CLM and EMOD validation.

<b>Variable</b>	<b>Period</b>	<b>Number of Samples</b>	<b>Source</b>
<b>Land Use</b>	July 2021	578	Site survey
<b>Larval Habitat</b>	2017-2021	769	Site survey
<b>Population</b>	2018-2021	-	Site survey
<b>Prevalence Rate</b>	January, October 2018; March, October 2019	4	Site survey
<b>Clinical Case</b>	April 2018-May 2020	26	Site survey

173 **Table S3.** Calibrated parameters in EMOD.

<b>Parameter</b>	<b>Value</b>
Antibody Memory Level	0.298
Base Sporozoite Survival Fraction	0.1667
Cytokine Gametocyte Inactivation	0.01335
Falciparum PfEMP1 Variants	150
Mean Sporozoites Per Bite	6
Merozoites Per Hepatocyte	990
Min Adapted Response	0.0174
Pyrogenic Threshold	500
Adult Life Expectancy	20
Male Life Expectancy	14
Aquatic Arrhenius 1	85,884,000,000

Aquatic Arrhenius 2	7,495
Infected Arrhenius 1	119,340,000,000
Infected Arrhenius 2	7,502
Scaling factor for larval capacity	$1.66 \times 10^{-5}$

174 **Table S4.** Spatial average of adult vector and parasite prevalence rate from the dry season  
 175 (November 2016 to April 2017) and the rainy season (May 2017 to October 2017).

Scenario	Dry Season		Rainy Season	
	Adult Vectors (# /km <sup>2</sup> )	Prevalence (Fraction)	Adult Vectors (# /km <sup>2</sup> )	Prevalence (Fraction)
Default EMOD	697	0.120	800	0.108
Integrated EMOD (Non-Irrigation)	451	0.111	961	0.107
Irrigation	889	0.154	1,140	0.182

176

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