

# Investigating the Impact of Irrigation on Malaria Vector Larval Habitats and Transmission using a Hydrology-based Model

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## Key Points:

- An agent-based malaria model was coupled with a hydrologic model to spatially simulate transmission by resolving habitat heterogeneity
- The coupling framework enhanced larval habitat area variability which resulted in a lower malaria transmission prediction
- Irrigation sustained transmission year-round, intensifying and shifting the peak forward by one month from the original period

**30 Abstract**

31 A combination of accelerated population growth and severe droughts have created pressure on  
32 food security and driven the development of irrigation schemes across sub-Saharan Africa.  
33 Irrigation has been associated with increased malaria risk, but it remains difficult to understand  
34 the underlying mechanism and develop countermeasures to mitigate its impact. While  
35 investigating transmission dynamics is helpful, malaria models cannot be applied directly in  
36 irrigated regions as they typically rely only on rainfall as a source of water to quantify larval  
37 habitats. By coupling a hydrologic model with an agent-based malaria model for a sugarcane  
38 plantation site in Arjo, Ethiopia, we demonstrated how incorporating hydrologic processes to  
39 estimate larval habitats can affect malaria transmission. Using the coupled model, we then  
40 examined the impact of an existing irrigation scheme on malaria transmission dynamics. The  
41 inclusion of hydrologic processes increased the variability of larval habitat area by around two-  
42 fold and resulted in reduction in malaria transmission by 60%. In addition, irrigation increased  
43 all habitat types in the dry season by up to 7.4 times. It converted temporary and semi-permanent  
44 habitats to permanent habitats during the rainy season, which grew by about 24%. Consequently,  
45 malaria transmission was sustained all-year round and intensified during the main transmission  
46 season, with the peak shifted forward by around one month. Lastly, we demonstrated how habitat  
47 heterogeneity could affect the spatiotemporal dynamics of malaria transmission. These findings  
48 could help larval source management by identifying transmission hotspots and prioritizing  
49 resources for malaria elimination planning.

50

**51 Plain Language Summary**

52 Population growth and severe droughts have driven the development of irrigation schemes across  
53 sub-Saharan Africa, which can increase malaria risk. The relationship between irrigation and  
54 malaria transmission dynamics remains unclear. Malaria models are seldom used to investigate  
55 this relationship as they typically rely only on rainfall to quantify larval habitats. By coupling a  
56 hydrologic model with a malaria model for a sugarcane plantation site in Arjo, Ethiopia, we  
57 demonstrated how incorporating hydrologic processes to estimate larval habitats can affect  
58 malaria transmission. Using the coupled model, we then examined the impact of the local  
59 irrigation on malaria transmission. The inclusion of hydrologic processes increased the  
60 variability of larval habitat area and resulted in a significant reduction in malaria transmission. In  
61 addition, irrigation increased all habitat types in the dry season and prolonged habitat stability  
62 during the rainy season. Consequently, malaria transmission was sustained year round and  
63 intensified during the main transmission season, with the peak shifted forward by around one  
64 month. Lastly, we demonstrated how habitat distribution could affect the spatiotemporal  
65 dynamics of malaria transmission. These findings could help identify mosquito breeding hotspots  
66 and prioritize resources for malaria elimination planning.

## 67 1. Introduction

68 Malaria is a deadly disease caused by parasites transmitted to humans through the bites of  
69 infected female *Anopheles* mosquitoes. It is particularly acute in sub-Saharan Africa and remains  
70 one of the region's most pressing public health challenges. About 95% of malaria cases and 96%  
71 of deaths in 2020 were recorded in sub-Saharan Africa (World Health Organization, 2021). A  
72 combination of accelerated population growth and arid conditions worsened by climate change  
73 has inevitably created pressure on food security (Ward et al., 2016). This drives the development  
74 of several regional irrigation schemes, which have been associated with increased malaria risk  
75 (Mangani et al., 2022). In past studies, the association has been chiefly demonstrated by  
76 statistical relationships based on field observations (Haileselassie et al., 2021; Kibret et al., 2014;  
77 Ondeto et al., 2022). However, these relationships may only be represented in some  
78 environmental settings because field observations are made at a limited number of discrete points  
79 in space and time.

80 Malaria modeling has the potential to complement field studies by exploring hypothetical  
81 scenarios and making a priori predictions that can inform intervention strategies. Originating  
82 from the basic Ross-Macdonald model (Ross, 1908), many compartmental models have inherited  
83 its simplifying assumptions, such as homogeneous biting and well-mixing of hosts and vectors,  
84 which is a shortcoming of representing the vectors and hosts as a population group rather than  
85 individuals (Reiner et al., 2013). In cases where spatial heterogeneity and stochasticity of disease  
86 progression are essential such as in a low-transmission setting, agent-based models (ABMs) can  
87 provide an explicit representation of individual actions and responses (N. R. Smith et al., 2018).  
88 Examples of advanced ABMs include Epidemiological MODeling (EMOD) (P. A. Eckhoff,  
89 2011), OpenMalaria (T. Smith et al., 2006), and a model developed at Imperial College (Griffin  
90 et al., 2010). While widely used in malaria intervention studies (Galactionova et al., 2021), these  
91 models tend to neglect the larval habitat representation (Griffin et al., 2010; T. Smith et al.,  
92 2006) or rely only on rainfall to quantify larval habitats (P. A. Eckhoff, 2011).

93 A recent study by Smith et al. demonstrated that using a hydrologic model to simulate  
94 habitat availability can uncover more complex patterns in climatic suitability for malaria  
95 transmission than applying a rainfall threshold (M. W. Smith et al., 2020). This is because the  
96 formation of larval habitats is heavily influenced by hydrologic processes, which are highly non-  
97 linear and spatially variable. In a hydrologic cycle, rainfall is partitioned into infiltration and  
98 surface runoff based on the soil type. Depending on the topography and surrounding vegetation,  
99 the resulting surface runoff will accumulate or drain. The persistence of the ponded water can  
100 also be influenced by evapotranspiration which varies with land use type. Besides rainfall,  
101 breeding sites can develop from groundwater, irrigation, reservoirs, and around dams. In  
102 irrigated settings, irrigation varies seasonally with crop production. Within a season, irrigation  
103 changes with local soil saturation and crop water use. The spatiotemporal variability of irrigation  
104 can result in habitats with different persistence and productivity. This diversity in habitat  
105 characteristics complicates the pattern of adult mosquito density and malaria transmission  
106 intensity (Frake et al., 2020; Hardy et al., 2013; Munga et al., 2006). Therefore, incorporating  
107 hydrologic processes into malaria modeling to capture habitat heterogeneity is essential and can  
108 help provide better insights into how irrigation affects malaria transmission.

109 There have been attempts to represent surface hydrology in malaria transmission  
110 modeling with varying levels of complexity and success (Ernest O. Asare et al., 2016). Most  
111 resort to a simple conceptual water balance model to determine the availability of water for

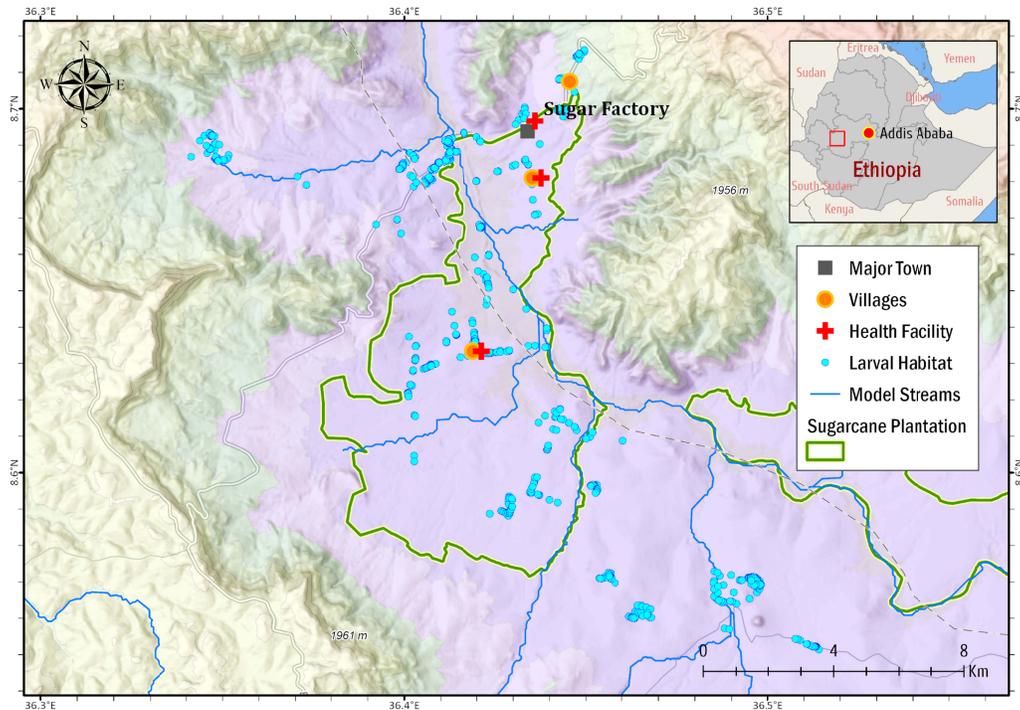
112 larval habitats (Ernest Ohene Asare et al., 2016; Montosi et al., 2012; Parham et al., 2012; Patz et  
113 al., 1998), while only a few have proposed more sophisticated hydrologic models that further  
114 consider canopy processes and subsurface flows (Bomblies et al., 2008; Le et al., 2018). Despite  
115 representing larval habitats more realistically, their malaria transmission component is often less  
116 comprehensive than advanced ABMs. Furthermore, none of these studies have investigated the  
117 impact of irrigation on malaria transmission.

118 In this study, we integrate a physical-based hydrologic model, ParFlow-Community Land  
119 Model (ParFlow-CLM) (Ashby & Falgout, 1996; Jones & Woodward, 2001; Kollet & Maxwell,  
120 2006; Maxwell, 2013; Maxwell & Kollet, 2008), with EMOD for a test site in Ethiopia. We  
121 chose EMOD because it is open-source and can be easily modified to assimilate inputs from an  
122 external hydrologic model. We aim to demonstrate how incorporating hydrologic processes to  
123 estimate larval habitats can affect malaria transmission intensity and seasonality. Using the  
124 coupled model, we then examine the impact of an existing irrigation scheme on the  
125 spatiotemporal dynamics of malaria transmission.

## 126 **2. Materials and Methods**

### 127 2.1. Study Site

128 We conducted this study in the Arjo-Didessa sugarcane plantation and its vicinity in the  
129 Didessa river valley, near Arjo town in Oromia Regional State, western Ethiopia (Figure 1). The  
130 study site includes a commercial sugar factory and an active irrigation area that relies on  
131 seasonal migrant workers for planting and harvesting. The site elevation ranges from 1,275 to  
132 2,105 m above sea level, with a mean annual rainfall of 1,560 mm from 1994 to 2020 (Figure  
133 S1). The primary rainy season is between May and October, and the dry season occurs for the  
134 rest of the year. Monthly average relative humidity varies widely from around 40% to 80%. It  
135 follows the rainfall pattern, while the monthly average temperature ranges from 19 °C to 24 °C  
136 and is lower in the rainy season than in the dry season (Figure S2). Flow and sprinkler irrigation  
137 are commonly practiced on the plantation (Fikadu, 2015). Due to poor drainage caused by the  
138 low permeability of the extensive heavy clay, the area is a perennial hotspot for larval habitats  
139 and is known to be malarious (Demissew et al., 2020; Hawaria et al., 2019). Malaria prevalence  
140 in this area is less than 3%, and transmission is seasonal, with cases peaking between September  
141 to December (Hawaria et al., 2019). *Anopheles arabiensis* is the primary malaria vector in this  
142 area. Local clinical malaria data shows that both major malaria parasites in Ethiopia,  
143 *Plasmodium falciparum* and *Plasmodium vivax*, co-exist with equal incidences but significant  
144 seasonality (Hawaria et al., 2019).



145  
 146 **Figure 1.** Arjo-Dedissa study site. The sugarcane plantation is demarcated in green within the  
 147 study site. The surveyed larval habitats, represented by the blue markers, were used to estimate  
 148 larval density and calibrate the hydrologic model. The three red crosses represent health facilities  
 149 frequented by plantation workers from nearby villages and provide clinical data for EMOD  
 150 calibration.

## 151 2.2. Data Collection

152 ParFlow-CLM requires climate data, including rainfall, short-wave radiation, long-wave  
 153 radiation, air temperature, surface pressure, specific humidity, and wind speeds, to drive the  
 154 hydrologic processes. The data were obtained from Precipitation Estimation from Remotely  
 155 Sensed Information using Artificial Neural Networks-Cloud Classification System-Climate Data  
 156 Record (PERSIANN-CCS-CDR) (Sadeghi et al., 2021) and the Fifth Generation European  
 157 Centre for Medium-Range Weather Forecasts Reanalysis (ERA5) (Hersbach et al., 2018). Air  
 158 temperature, humidity, and long-wave radiation were adjusted to account for the mismatch in  
 159 surface elevation between ERA5 and the study area, following the method by Cosgrove et al.  
 160 (2003). For processes at the land surface, topography was obtained from a commercial global  
 161 digital elevation model, ALOS World 3D (Takaku & Tadono, 2017) with additional hydro-  
 162 conditioning (Jiang et al., 2023), and land cover information was extracted from Global Land  
 163 Cover Mapping Project, which is based on Landsat and Chinese HJ-1 satellite images (Chen et  
 164 al., 2015). To characterize the subsurface, soil properties were referenced from the  
 165 SoilGrids250m TAXOUSA dataset (Hengl et al., 2017) for the top 2 m from the surface, and  
 166 the parameters for the deeper geological layer beyond the top 2 m were defined using  
 167 GLHYMPS 2.0 (Gleeson et al., 2014). The bottom of the geological layer was delineated based  
 168 on the depth to bedrock data from SoilGrids250m (Hengl et al., 2017). The climate inputs for  
 169 EMOD include rainfall, air temperature, land temperature, and humidity. The rainfall data were

170 similarly obtained from PERSIANN-CCS-CDR, and the others were extracted from ERA5. The  
171 list of model input data can be found in Table S1.

172 Besides publicly available data, several field surveys were conducted to support model  
173 development (Table S2). In previous studies, larval habitat data were collected over seasonal  
174 campaigns from 2017 to 2021, with a total of 769 sampled points (Hawaria et al., 2020). The  
175 larval habitat survey was conducted within 500 meters of the village boundaries and sugarcane  
176 plantations. The surveyed larval habitat locations are shown in Figure 1. Mosquito larvae were  
177 sampled following the World Health Organization (WHO) standard larval survey procedure  
178 using a standard dipper (350 ml). Larvae were identified morphologically and sorted by genus as  
179 *Anopheles* or *Culex* in the field. From the survey, habitat locations within the hydrologic  
180 modeling domain were used to validate the predicted aquatic habitats simulated in ParFlow-  
181 CLM, and larval density was used to determine the larval carrying capacity of the habitats in  
182 EMOD. In addition to the larval habitat survey, a land cover field survey was conducted in July  
183 2021 in the study area. The survey was performed every 400 meters along the perpendicular  
184 transects, spaced every 2 km apart along each of the 12 major road segments, with a total of 400  
185 survey points (Figure S3). Survey results were collected with Open Data Kit (Hartung et al.,  
186 2010) and used to validate satellite imagery. The most common land cover type in the study area  
187 was cropland and natural vegetation mosaics (Figure S4).

188 To configure the parameters in EMOD and validate the model, population data, malaria  
189 incidence, and parasite prevalence rates were collected from previous works. Population data  
190 were obtained from demographic surveys in the sugar factory command village and vicinity  
191 communities from 2018 to 2021. Clinical cases for the 2008 to 2017 period were referenced from  
192 the malaria morbidity registration books (Hawaria et al., 2019). The prevalence rate was  
193 calculated based on passive case detection implemented at the Arjo Sugar Factory Clinic and two  
194 other health facilities in 2018 and 2019. Since there were no official records of malaria control  
195 campaigns in the study area for the past 20 years, we also interviewed the district health officers,  
196 clinical staff in health facilities, and sugar factory administrations to estimate the coverage,  
197 duration, and the total number of long-lasting insecticidal bed nets (LLIN) distributed and indoor  
198 residual spraying (IRS) applied (personal communication, April 30, 2022).

## 199 2.3. Model Approach

### 200 2.3.1. Model Background

201 We used ParFlow-CLM, a process-based gridded model, to simulate hydrologic  
202 processes in the Arjo study site in Ethiopia. ParFlow solves the variably saturated subsurface  
203 flow and overland flow, while CLM calculates the canopy water balance and terrestrial energy  
204 balance, which are influenced by land cover characteristics. Due to its ability to simulate  
205 complex surface-subsurface interactions, ParFlow-CLM can resolve a diverse range of water  
206 bodies driven by heterogenous hydrological and geomorphological processes, which result in  
207 different breeding habitats such as rain-fed pools, flood basins, and spring-fed ponds (M. W.  
208 Smith et al., 2013).

209 EMOD was used to simulate malaria transmission in the study area. The modeled region  
210 in EMOD can be represented as a single node or divided into multiple nodes. As a stochastic  
211 ABM, it simulates the simultaneous interactions between humans and mosquitoes within each  
212 node, using decision rules based on individual agent properties with inbuilt randomness (Bill &

213 Melinda Gates Foundation, 2022). The properties are defined by user inputs on demographic,  
 214 climate, mosquito, parasite, and intervention parameters. The model simulates vector population  
 215 dynamics (e.g., vector life cycle, vector survival and feeding), human population dynamics,  
 216 human immunity, within-host parasite dynamics, and effects of interventions such as antimalarial  
 217 drugs and vaccines (P. Eckhoff, 2013).

### 218 2.3.2. Linking Habitat Representation in EMOD with ParFlow-CLM

219 In EMOD, natural larval habitats commonly comprise temporary, semi-permanent and  
 220 permanent (constant) habitats, and each habitat type is calculated based on a different equation  
 221 (P. A. Eckhoff, 2011). Temporary habitats are driven mainly by rainfall and decay at a rate  
 222 proportional to the evaporation rate, which is a function of temperature and humidity. The area  
 223 of temporary habitats in each node at time  $t$ ,  $H_{temp}^t$ , is calculated by:

$$224 \quad H_{temp}^t = H_{temp}^{t-1} + \lambda_{temp} P^t D_{cell}^2 - H_{temp}^{t-1} \tau_{temp}^t \Delta t \quad (1)$$

225 and

$$226 \quad \tau_{temp}^t = 5.1 \times 10^{11} e^{\frac{-5628.1}{T^t}} k_{temp} \sqrt{\frac{0.018}{2\pi R T^t}} (1 - RH^t), \quad (2)$$

227 where  $\lambda_{temp}$  is a scaling factor,  $P^t$  is rainfall at time  $t$ ,  $\tau_{temp}^t$  is a decay rate at time  $t$ ,  $D_{cell}$  is the  
 228 nodal size in degree,  $\Delta t$  is the time interval,  $T^t$  is the temperature in Kelvin at time  $t$ ,  $k_{temp}$  is a  
 229 decay factor,  $R$  is the universal gas constant 8.314 J/mol/K and  $RH^t$  is the relative humidity at  
 230 time  $t$ .

231 Similar to temporary habitats, semi-permanent habitats are also driven by rainfall, but the  
 232 decay rate is a constant that is independent of temperature and humidity. Semi-permanent  
 233 habitats are configured to decay slower than temporary habitats. Using a scaling factor  $\lambda_{semi}$  and  
 234 a decay rate  $\tau_{semi}$ , the area of semi-permanent habitats  $H_{semi}^t$  is calculated as:

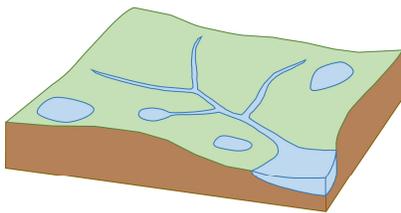
$$235 \quad H_{semi}^t = H_{semi}^{t-1} + \lambda_{semi} P^t D_{cell}^2 - H_{semi}^{t-1} \tau_{semi} \Delta t, \quad (3)$$

236 Lastly, permanent habitats are assumed to be independent of rainfall, temperature, and  
 237 humidity. The area,  $H_{perm}^t$ , remains the same over time and is determined by a constant  $\lambda_{perm}$ :

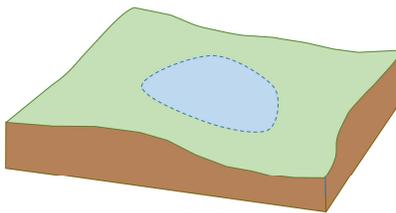
$$238 \quad H_{perm}^t = \lambda_{perm} D_{cell}^2, \quad (4)$$

239 As shown in Figure 2, EMOD conceptually models each habitat type within a node as a  
 240 lumped habitat which is oversimplified and does not have the granularity to support habitat-  
 241 based interventions. To enhance the fidelity of the model in representing habitats which are  
 242 spatially distributed in reality, we simulated the habitats explicitly in ParFlow-CLM in place of  
 243 the default habitat calculation in EMOD.

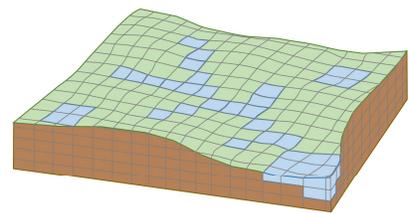
(a) Field Habitats



(b) EMOD Habitats



(c) ParFlow-CLM Habitats



244

245 **Figure 2.** Illustration of (a) field habitats within a study area (b) conceptually lumped habitat  
 246 calculated in EMOD within a node representing the same study area (c) spatially distributed  
 247 habitats simulated in Parflow-CLM within the same node.

248 ParFlow-CLM generated the spatiotemporal distribution of surface soil saturation, which  
 249 was used to determine the availability of surface water that could contribute to ponding. For each  
 250 grid cell in ParFlow-CLM, ponding was assumed to occur if the soil saturation exceeds a  
 251 threshold,  $\theta$ , which was calibrated based on larval habitat observations. The duration of ponding  
 252 was quantified and referred to as the Wetness Index. Based on the Wetness Index, each cell was  
 253 classified into temporary (15-90 days), semi-permanent (90-180 days) or permanent habitat  
 254 (more than 180 days). Rivers with high flow rates were not considered since *Anopheles* larvae  
 255 have a lower chance of surviving in fast-moving water (Hardy et al., 2013). Details of the  
 256 concept of hydrologic simulation and larval habitat identification can be found in Jiang et al.  
 257 (2021). For each time step, the fraction of the study area covered by each habitat type (i.e.,  
 258  $F_{temp}^t$ ,  $F_{semi}^t$ , and  $F_{perm}^t$ ) was calculated and input into EMOD. Finally, the area for each habitat  
 259 type in each node was obtained after multiplying the fractional area coverage by the nodal area  
 260 as follows:

$$261 \quad H_{temp}^t = F_{temp}^t D_{cell}^2, \quad (5)$$

$$262 \quad H_{semi}^t = F_{semi}^t D_{cell}^2, \quad (6)$$

263 and

$$264 \quad H_{perm}^t = F_{perm}^t D_{cell}^2, \quad (7)$$

265 where  $F_{temp}^t$ ,  $F_{semi}^t$ ,  $F_{perm}^t$  are the fractional area coverage of temporary, semi-permanent, and  
 266 permanent habitats, respectively.

### 267 2.3.3. Habitat Larval Capacity

268 EMOD requires the user to define a larval capacity per unit area ( $LC$ ) for each habitat  
 269 type, representing the maximum hypothetical number of larvae that can co-exist within a 1-  
 270 degree by 1-degree habitat area.  $LC$  was then multiplied by the nodal time series habitat area in  
 271 degree<sup>2</sup> (Section 2.3.2). Finally, the variation in larval capacity within a node is defined.

272 In this study,  $LC$  was estimated using field survey data for each habitat type (Text S1). In  
 273 Table 1,  $LD_{dip}$  represents the larval density in number of larvae per dip. We then converted  
 274  $LD_{dip}$  to an equivalent number of larvae per unit degree squared,  $LD$ , based on the opening area  
 275 of the standard 350 ml mosquito larvae dipper, which is 13 cm in diameter (Orondo et al., 2023).  
 276 To obtain  $LC$ , we adjusted  $LD$  by a scaling factor,  $s$ , during the calibration of EMOD. The  
 277 adjustment is necessary because using  $LD$  directly will overestimate the larval capacity as  
 278 surveyors tend to dip at locations with a higher density of larvae within a sampled habitat.

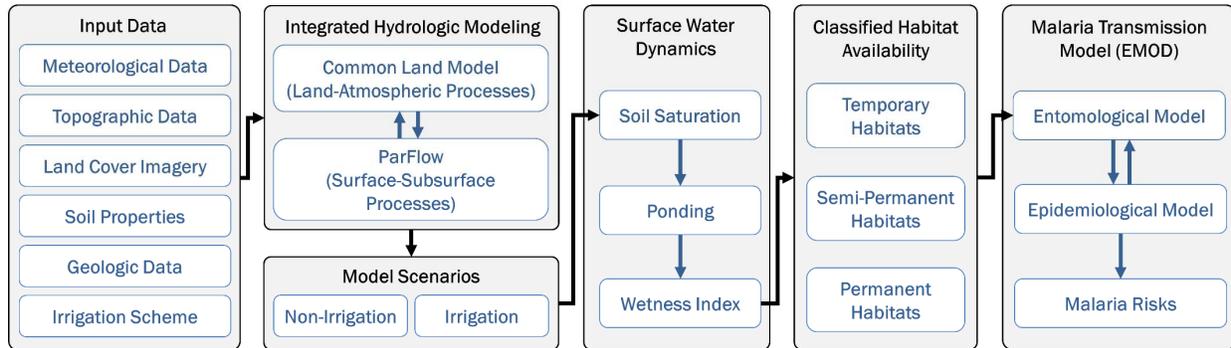
279 **Table 1.** Laval density derived from field survey and calibrated larval capacity per unit area for  
 280 each habitat type.

Habitat Type	Larval Density		Larval Capacity per Unit Area
	$LD_{dip}$ (#/dip)	$LD$ (#/degree <sup>2</sup> )	$LC = s \times LD$ (#/degree <sup>2</sup> )

Temporary	0.167	$1.97 \times 10^{11}$	$3.27 \times 10^6$
Semi-Permanent	0.089	$1.05 \times 10^{11}$	$1.74 \times 10^6$
Permanent	0.440	$5.18 \times 10^{11}$	$8.62 \times 10^6$

281

282 In summary, we identified potential larval habitats in ParFlow-CLM and classified them  
 283 into temporary, semi-permanent, and permanent habitats as an input to the vector cycle  
 284 simulation in EMOD. The overall schematic of our modeling approach is shown in Figure 3.



285

286

**Figure 3.** Framework for integrating ParFlow-CLM with EMOD.

## 287 2.4. Model Configuration

### 288 2.4.1. Model Domain

289 In a previous study, ParFlow-CLM was successfully applied in Arjo for larval habitat  
 290 identification over one year through 2018 (Jiang et al., 2021). Here, we expanded the hydrologic  
 291 simulation to 20 years from 2000 to 2020. The model domain area was 208 km<sup>2</sup> (Figure 1). To  
 292 keep the computational time manageable, we decreased the spatial resolution from 50 m to 100  
 293 m and reduced the number of subsurface layers from 10 to 5 layers. The thickness of the layer  
 294 from ground surface to bedrock was 0.1 m, 0.3 m, 0.6 m, 1 m, and 78 m, over a total vertical  
 295 depth of 80 m.

296 For malaria transmission modeling in EMOD, we focused on the sugarcane plantation  
 297 area within the hydrologic modeling domain (Figure 1). The EMOD domain was configured as a  
 298 single node measuring 10 km by 10 km.

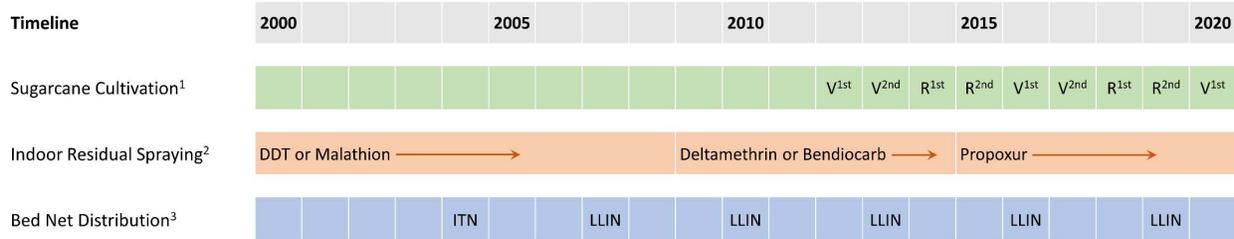
### 299 2.4.2. Model Scenarios

300 Three model scenarios were developed for this study. In the first scenario (*Default*  
 301 *EMOD*), malaria transmission was simulated based on the default larval habitat equations in  
 302 EMOD (Equations (1) to (4)). In the second scenario (*Integrated EMOD or Non-Irrigation*), the  
 303 default larval habitat equations were replaced by the simulated habitats from ParFlow-CLM  
 304 through Equations (5) to (7), which integrates terrestrial hydrological processes. To investigate  
 305 the effect of irrigation, a third scenario (*Irrigation*) was added using the same integrated  
 306 approach from the second scenario, but irrigation was modeled in ParFlow-CLM per the local  
 307 schedule as described below.

308 Irrigation was applied starting in 2012, and a 4-year sugarcane planting cycle was  
 309 adopted in the model, as shown in Figure 4. The cycle includes a 2-year cycle for virgins and two

310 1-year cycles for ratoons, typical of the sugarcane plantation. The irrigation scheme was  
 311 designed based on the sugarcane planting cycle, and the months with irrigation are shown in  
 312 Figure S6. During the irrigating season, irrigation occurred every 10 days for the first 3 days.  
 313 Daily 5.3 mm/hr of sprinkler water was applied for 22 hours. The derivation of the irrigation rate  
 314 can be found in Text S2.

315 In the three scenarios, malaria interventions, including IRS and bed net distribution, were  
 316 modeled per the schedule shown in Figure 4.



<sup>1</sup> V<sup>1st</sup> and V<sup>2nd</sup>: First and second year of virgin planting; R<sup>1st</sup> and R<sup>2nd</sup>: First and second year of ratoon planting.

<sup>2</sup> DDT: Dichlorodiphenyltrichloroethane.

<sup>3</sup> ITN: Insecticide-treated net (permethrin); LLIN: Long-lasting insecticidal net.

317  
 318 **Figure 4.** Configuration of intervention and sugarcane cultivating plan in the integrated model.  
 319 The irrigation schedule can be referred to in Text S2 and Figure S6.

320 As it is challenging to ascertain the total area of the habitats in the study area, the scaling  
 321 factors ( $\lambda_{temp}$ ,  $\lambda_{semi}$  and  $\lambda_{perm}$ ) in *Default EMOD* were set individually such that the average  
 322 area of each habitat type over the simulation period was the same as *Integrated EMOD* to allow a  
 323 fair comparison. In addition, the decay parameters  $k_{temp}$  and  $\tau_{semi}$  in *Default EMOD* were also  
 324 adjusted to match the variability in *Integrated EMOD* (Figure S7).

### 325 2.4.3. Model Calibration

326 We calibrated ParFlow-CLM and EMOD in the *Irrigation* scenario and used the same  
 327 calibrated parameters in the *Default EMOD* and *Integrated EMOD* scenarios. This is because  
 328 observed data was only available for the period after irrigation was implemented in the study  
 329 area. This also prevented the effect of incorporating hydrologic modeling or irrigation from  
 330 being obscured by using different parameters in each scenario.

331 As the spatial resolution in ParFlow-CLM was modified from the previous study (Jiang et  
 332 al., 2021), we recalibrated the saturation threshold,  $\theta$ . The calibration was to ensure that the  
 333 model will predict the occurrence of ponding at locations in line with the field surveyed larval  
 334 habitats for soil saturation above the selected threshold (Text S3 and Jiang et al., 2021). For the  
 335 calibration of EMOD, we identified 15 key parameters (Table S3) after a preliminary sensitivity  
 336 analysis. The calibration aimed to align the simulated prevalence rate and pattern of clinical  
 337 cases with local data (Text S3). The rest of the parameters were either referenced from published  
 338 studies (Gerardin et al., 2015; Selvaraj et al., 2018) or set based on default values in EMOD.

### 339 2.4.4. Spatial Realization of Transmission through Heterogeneity of Habitats

340 To demonstrate how the heterogeneity of habitats can affect malaria transmission, we  
 341 conducted an additional analysis by discretizing the study site into 100 nodes measuring 1 km by  
 342 1 km in EMOD. All the nodes were assigned the same calibrated parameters, but the input

343 habitat was specific to the area covered by each node. This was only applicable to the scenarios  
344 with ParFlow-CLM integrated into EMOD. The habitat simulation in *Default EMOD* could not  
345 reflect spatial heterogeneity since it cannot process the effects of topography, soil and land cover.

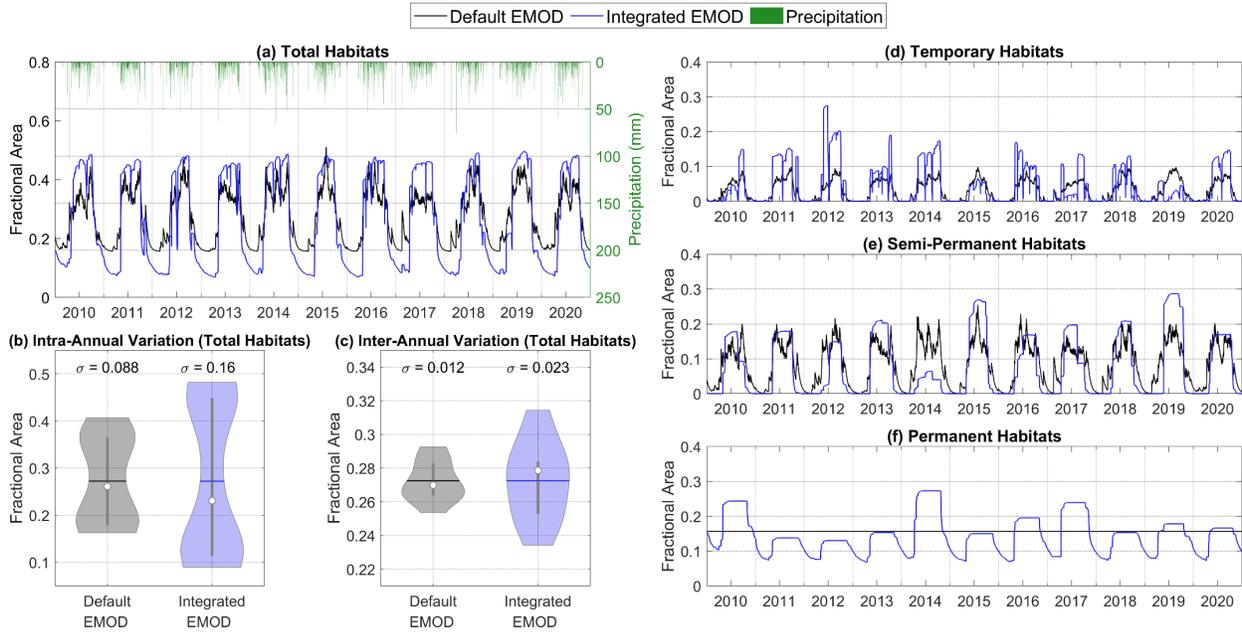
### 346 **3. Results**

#### 347 3.1. Effect of Hydrology on Larval Habitats and Malaria Transmission

348 A comparison of the larval habitat area as a fraction of the study area between *Default*  
349 *EMOD* and *Integrated EMOD* is illustrated in Figure 5. In both scenarios, the total larval habitat  
350 area varied in tandem with seasonal rainfall, with a mean of 27% (Figure 5a). However, the  
351 habitats in *Integrated EMOD* exhibited less frequent daily fluctuations, and its seasonal range  
352 was more extensive than *Default EMOD*. Figure 5b shows a violin plot of the average total  
353 habitats for each day within a year (intra-annual distribution). In contrast, Figure 5c shows a  
354 violin plot of the annual average total habitats (inter-annual distribution) throughout the  
355 simulation period. The habitats in *Integrated EMOD* were found to have a more significant intra-  
356 annual and inter-annual variability as the standard deviation of the habitats is about 1.8 times and  
357 2 times that of *Default EMOD*, respectively. The reason is attributable to the simplifying  
358 assumptions built into the habitat functions in *Default EMOD* and will be discussed further in  
359 Section 4.1.

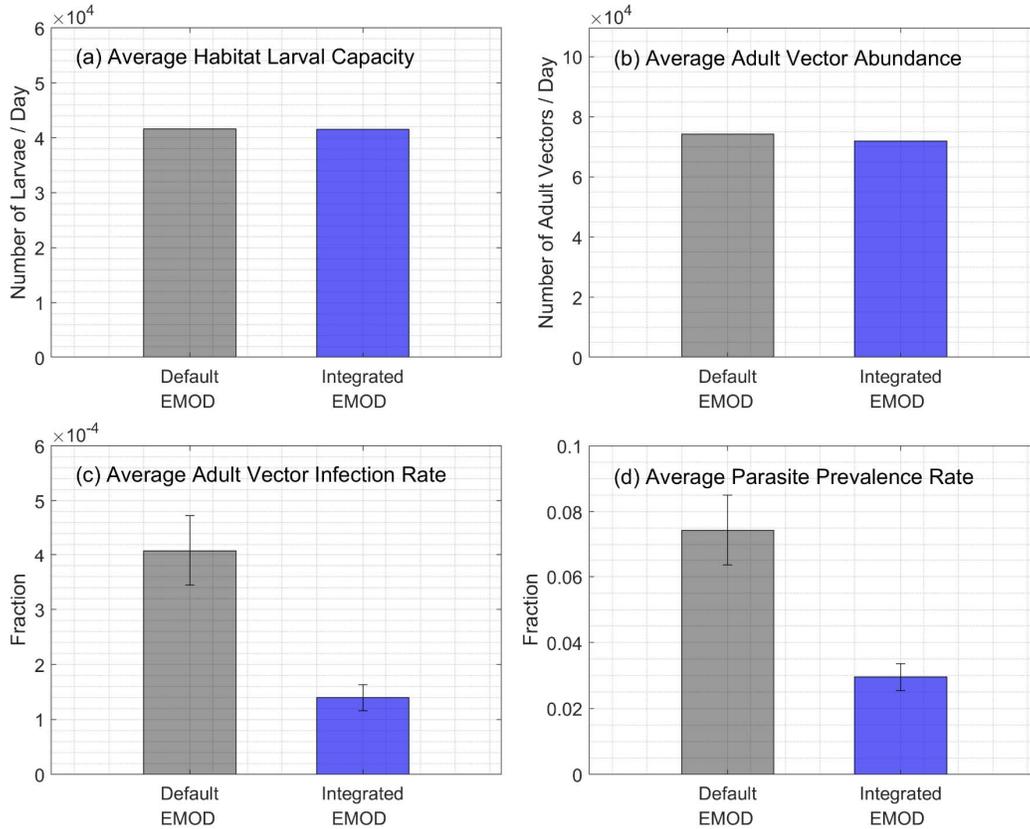
360 Figure 5d, Figure 5e, and Figure 5f present the breakdown for each habitat type. Of the  
361 total larval habitat area, permanent habitats were the most dominant, accounting for 16% of the  
362 study area, followed by semi-permanent habitats (8.4%) and temporary habitats (3.3%). In  
363 *Integrated EMOD*, the fluctuation in habitat area gradually becomes smoother from temporary to  
364 semi-permanent and finally permanent habitats, corresponding with the increasing stability of the  
365 habitats. In each year, the distribution between the habitat types can vary significantly depending  
366 on the magnitude and duration of rainfall in that year. For example, there were more temporary  
367 habitats relative to semi-permanent habitats in 2012 and vice-versa in 2015 due to a difference in  
368 rainfall patterns.

369 In contrast, the difference in stability and dynamic distribution between temporary and  
370 semi-permanent habitats was less apparent in *Default EMOD*. Notably, the area of permanent  
371 habitats remained constant throughout the years. This is a key difference from *Integrated*  
372 *EMOD*, in which permanent habitats were defined as habitats with more than 180 days of  
373 ponding and subject to temporal variations.



374  
 375 **Figure 5.** Comparison of daily simulated larval habitat area between *Default EMOD* and  
 376 *Integrated EMOD* from 2010 to 2020. The simulation was performed for 20 years from 2000 to  
 377 2020, but here we only show the results from 2010 to 2020 for simplicity. (a) The total habitat  
 378 area is broken down into (d) temporary habitats, (e) semi-permanent habitats and (f) permanent  
 379 habitats. Violin plots were used to illustrate the (b) intra-annual distribution and (c) inter-annual  
 380 distribution of the total habitat area. Intra-annual distribution is based on the 20-year average  
 381 habitat area for each day of a year, while inter-annual distribution is characterized by the annual  
 382 average habitat area for each year. In the violin plots, the white dot and horizontal line represent  
 383 the median and mean, respectively. The vertical bar in the center of the violin plot corresponds to  
 384 the interquartile range.

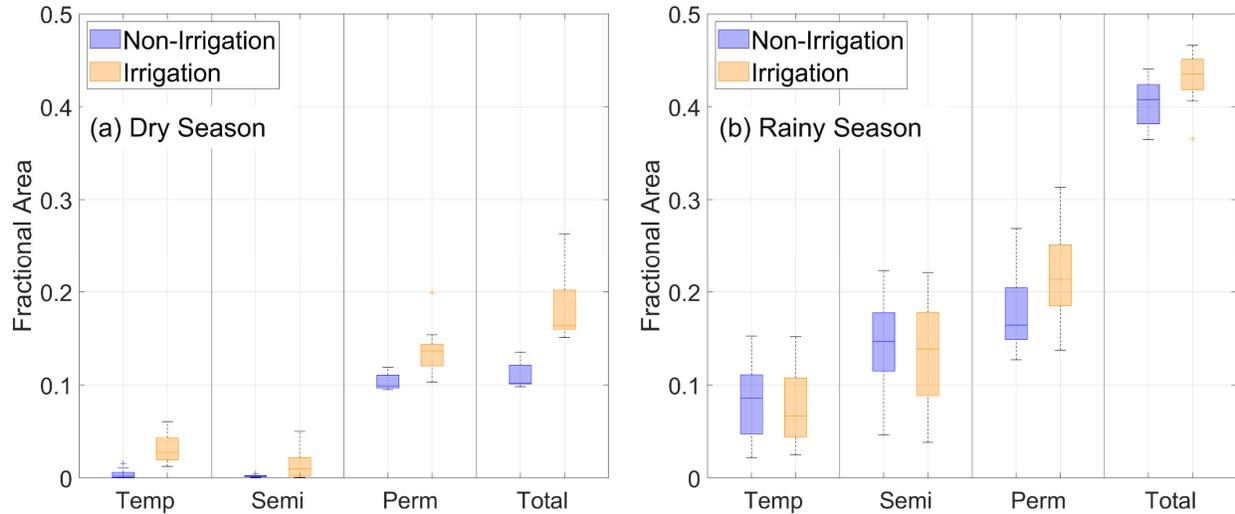
385 Since the average total larval habitat area was the same in *Default EMOD* and *Integrated*  
 386 *EMOD*, the average habitat larval capacity was identical in both scenarios (Figure 6a). However,  
 387 the number of adult vectors was slightly higher (by 3%) in the "Default EMOD" scenario (Figure  
 388 6b). The resulting difference was further amplified to 2.9 times for the average vector infection  
 389 rate (Figure 6c) and 2.5 times for the average prevalence rate (Figure 6d). Given that all other  
 390 input data and parameters in EMOD were the same, this can be attributed to the visibly lower  
 391 variability in the daily habitat larval capacity of *Default EMOD* (Figure S11c), providing a stable  
 392 environment for the vector to thrive throughout the year. The lower variability in habitat larval  
 393 capacity is not only due to lower variability in larval habitat area but also the high larval capacity  
 394 per unit area of permanent habitats whose area does not vary. In summary, the results suggest  
 395 that incorporating hydrologic modeling can produce higher variability in larval habitat, resulting  
 396 in lower simulated malaria transmission.



397  
 398 **Figure 6.** Comparison of annual average malaria transmission indicators between *Default*  
 399 *EMOD* and *Integrated EMOD* from 2000 to 2020. The indicators include (a) habitat larval  
 400 capacity, (b) adult vector abundance, (c) adult vector infection rate, and (d) parasite prevalence  
 401 rate.

### 402 3.2. Effect of Irrigation on Larval Habitats and Malaria Transmission

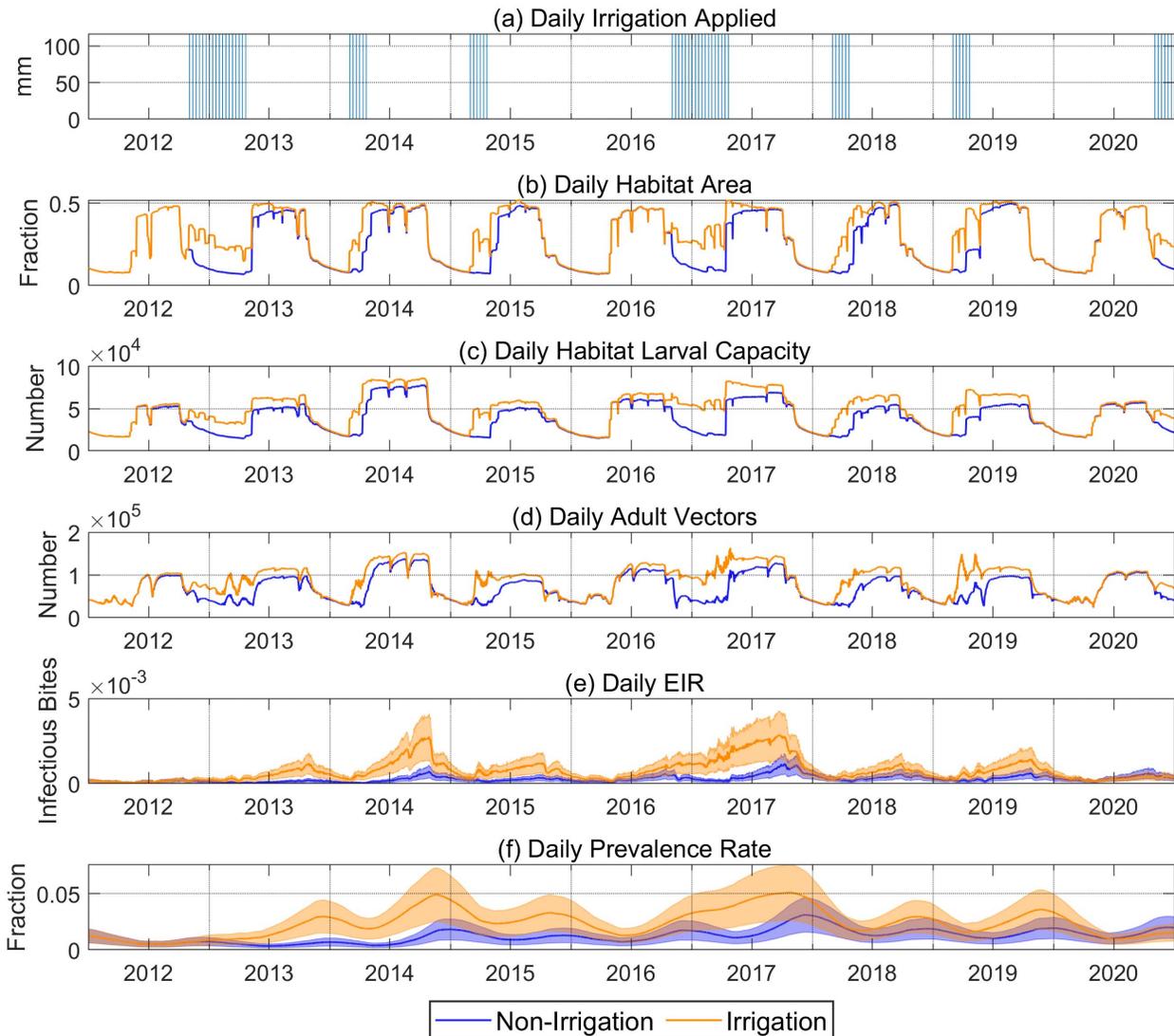
403 Irrigation generally increased the habitat area in both dry and rainy seasons. In the dry  
 404 season (Figure 7a), the increase in median fractional area was the highest for temporary habitats  
 405 (7.4 times), followed by semi-permanent habitats (6.6 times) and permanent habitats (1.3 times).  
 406 Although irrigation was only applied in the dry season, it prolonged the stability of temporary  
 407 and semi-permanent habitats and converted them to permanent habitats in the rainy season  
 408 (Figure 7b). Temporary and semi-permanent habitats decreased in coverage by about 7% and  
 409 8%, whereas permanent habitats grew by 24%. From the results, habitats arising from irrigation  
 410 may enable the development of vectors in the dry season while stabilizing the growth in rainy  
 411 seasons.



412 **Figure 7.** Comparison of larval habitat area during (a) dry season and (b) rainy season from 2012  
 413 to 2020 between *Non-Irrigation* and *Irrigation*. Habitats are further classified into temporary,  
 414 semi-permanent, and permanent types. The horizontal line inside the box represents the median,  
 415 and the height of the box corresponds to the interquartile range.  
 416

417 Next, we presented the simulated times series of habitat area, larval capacity, adult vector  
 418 population, entomological inoculation rate (EIR), and parasite prevalence for *Non-Irrigation* and  
 419 *Irrigation* over the irrigated period in Figure 8. Comparing Figure 8b and Figure 8c, the  
 420 differences in the larval capacity per unit area for each habitat type introduce more inter-annual  
 421 variability to larval capacity as the relative abundance of each habitat type is dynamic. The adult  
 422 vector population's pattern generally follows habitat larval capacity. However, the EIR cycle lags  
 423 the adult vector population cycle by 2 months, and the parasite prevalence cycle lags the EIR  
 424 cycle by another 1 month.

425 The increase in habitat area arising from the applied irrigation contributed to an increase  
 426 in adult vector population beyond the irrigation periods as well as EIR and parasite prevalence.  
 427 The simulated daily EIR hit a maximum of 0.0029 in September 2017, a 3-fold increase  
 428 compared to *Non-Irrigation*, due to the longest preceding irrigation period. In the same year, the  
 429 maximum prevalence occurred in October, with a 1.9-fold increase to 0.0509. It was also found  
 430 that the EIR and prevalence peaks, which occurred around October/November and  
 431 November/December, respectively, were shifted forward by about one month after irrigation was  
 432 applied.



433  
 434 **Figure 8.** Time series of daily applied irrigation in *Irrigation* and comparison of simulated daily  
 435 malaria transmission results between *Non-Irrigation* and *Irrigation*. Malaria transmission results  
 436 include (b) habitat area, (c) habitat larval capacity, (d) adult vector abundance, (e) entomological  
 437 inoculation rate, and (f) parasite prevalence rate. The simulation was performed for 20 years  
 438 from 2000 to 2020, but here we only show the results from 2012 onwards, when irrigation began.

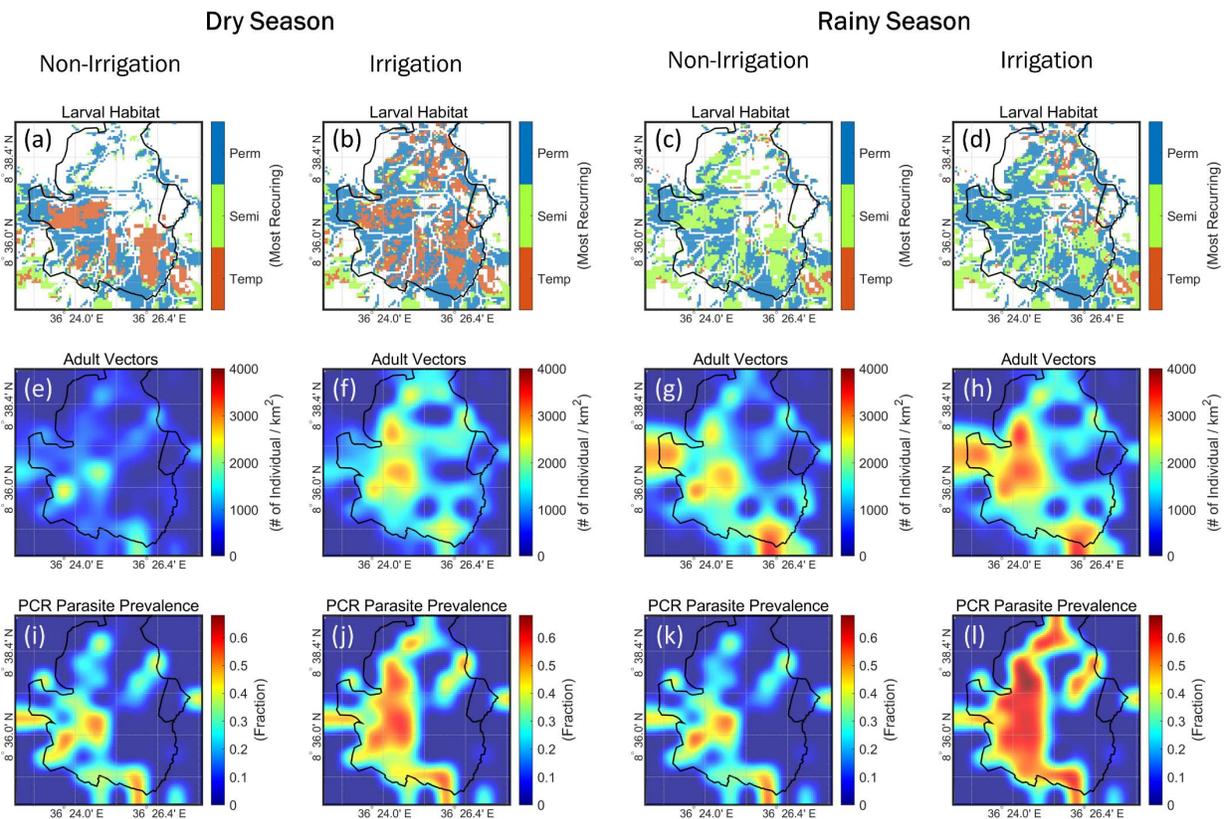
### 439 3.3. Spatial Variation of Malaria Transmission

440 The effect of the spatial distribution of larval habitats on malaria transmission is  
 441 illustrated in Figure 9. Larval habitats formed more easily in the southwestern region (Figure 9a-  
 442 d) which is characterized by clay-rich soil with low permeability (Figure S12). Besides soil type,  
 443 the distribution of the habitat types within the study area varied substantially with hydrologic  
 444 processes depending on the local topography, land use, and irrigation. In both dry and rainy  
 445 seasons, irrigation expanded the area covered by habitats and increased the stability of existing  
 446 habitats.

447 Like habitat areas, the adult vector hotspots in both seasons were enlarged and intensified  
 448 by irrigation (Figure 9e-h). The increase in vector population was more significant in the dry

449 season (Table S4) due to the creation of more habitats by irrigation. The adult vector hotspots  
 450 were mainly concentrated around permanent habitats configured with the highest larval capacity  
 451 based on field data.

452 In general, irrigation increased the prevalence rate difference between the rainy and dry  
 453 seasons. Without irrigation, the parasite prevalence cycle peaked shortly after the rainy season in  
 454 November and December, which are considered part of the dry season (Figure 8d and Figure 8f).  
 455 Due to the time lag, although the adult vector population was higher in the rainy season than the  
 456 dry season, this difference became less apparent when comparing the prevalence rates between  
 457 the two seasons (Figure 9i and Figure 9k). In 2017, irrigation was applied from November 2016  
 458 to April 2017, connecting two rainy seasons and creating favorable conditions for breeding over  
 459 more than a year (Figure 8c). As a result, the prevalence in the second rainy season from May  
 460 2017 to October 2017 (Figure 9l) was visibly higher than the preceding dry season (Figure 9j).  
 461 This indicates that irrigation can introduce a compounding effect on malaria transmission and  
 462 alter its seasonal distribution.



463  
 464 **Figure 9.** Spatial distribution of daily average larval habitats, adult vectors, and parasite  
 465 prevalence diagnosed by Polymerase Chain Reaction (PCR) in the dry season (November 2016-  
 466 April 2017) and the rainy season (May 2017-October 2017). This period was selected because  
 467 the effect of irrigation on malaria transmission was the most pronounced. The simulated larval  
 468 habitats, adult vectors, and PCR parasite prevalence from *Non-Irrigation* are presented in (a), (e)  
 469 and (i) for the dry season and (c), (g) and (k) for the rainy season. Similarly, the simulated larval  
 470 habitats, adult vectors and PCR parasite prevalence from *Irrigation* are presented in (b), (f) and

471 (j) for the dry season and (d), (h) and (l) for the rainy season. Their spatially averaged values can  
 472 be found in Table S4.

#### 473 4. Discussion

##### 474 4.1. Role of Hydrology in Degree of Habitat Seasonality and Implications on Transmission

475 The average vector infection and prevalence rates in *Default EMOD* over the simulation  
 476 period were significantly higher than *Integrated EMOD*. From Figure 5a, one of the most  
 477 noticeable differences between the two scenarios was the degree of seasonality of the larval  
 478 habitat. Although the mean habitat area was set the same in both scenarios, the magnitude of the  
 479 seasonal variation was larger when hydrologic modeling was incorporated. This is mainly  
 480 because the hydrologic model in *Integrated EMOD* considers complex physical processes and  
 481 characteristics specific to the study area, including topography, land use, and soil. At the same  
 482 time, *Default EMOD* adopts a parsimonious, one-size-fits-all approach. Specifically, the default  
 483 habitat function in EMOD assumed that the permanent habitat area was at equilibrium and  
 484 remained constant throughout the simulation. In reality, permanent habitats such as those on  
 485 river edges can vary in the area with climate conditions. In addition, there was no infiltration  
 486 mechanism for the other two habitat types (Equation (1) and Equation (3)), so new ponds started  
 487 forming immediately at the onset of the rainy season and continued forming towards the end of  
 488 the rainy season whenever there was rainfall. The result was an earlier rising limb and a delayed  
 489 falling limb in the time series compared to *Integrated EMOD* (see Figure S13 for an example).  
 490 As the mean area in both scenarios was the same, the *Default EMOD* time series naturally ended  
 491 up with a broader but flatter crest.

492 Due to the high larval capacity for permanent habitats, the habitat larval capacity time  
 493 series in *Default EMOD* becomes even more invariant (Figure S11c). Therefore, to evaluate the  
 494 effect of the degree of seasonality in the larval habitat on malaria transmission, we conducted a  
 495 sensitivity analysis using a synthetic sinusoidal time series for larval habitat fractional area with  
 496 the same mean but different amplitudes:

$$497 F_{\alpha}^t = \alpha \cos(365.25t + 125.2) + \bar{F}, \quad (6)$$

498 where  $\alpha$  is the amplitude of fractional area,  $F_{\alpha}^t$  is the fractional area at time  $t$ ,  $\bar{F}$  is the mean  
 499 fractional area specific to the study derived from the hydrologic model.

500 The sensitivity analysis results can be found in Figure S14 and are summarized in Table  
 501 2. By reducing the seasonal amplitude from 0.2 to 0.1, the adult vector population remained  
 502 relatively unchanged, but the vector infection and prevalence rates tripled. For the extreme case  
 503 when  $\alpha$  was reduced to 0, the vector infection and prevalence rates increased further by 4.29  
 504 times and 4.80 times, respectively. This finding agrees with the higher simulated malaria  
 505 transmission in *Default EMOD* compared to *Integrated EMOD* (Figure S11e-g). It is possible  
 506 that in the case where  $\alpha$  was 0, the consistent adult vector population arising from the invariant  
 507 habitat availability resulted in a stable parasite transmission throughout the year. As  $\alpha$  increased,  
 508 the disparity between the high and low vector abundance seasons increased. In the low vector  
 509 abundance season, the transmission was minimal. In the high vector abundance season,  
 510 transmission increased but would be limited by the human population. This resulted in an overall  
 511 lower annual average vector infection rate and prevalence. Therefore, a nuanced approach

512 considering the trend of the mean and the degree of the seasonality of larval habitats is required  
 513 to predict malaria transmission accurately.

514 **Table 2.** Average simulated adult vector abundance, adult vector infection rate, and parasite  
 515 prevalence rate for different amplitudes of larval habitat seasonality,  $\alpha$ .

$\alpha$	Adult Vectors	Vectors Infection Rate	Parasite Prevalence Rate
0.2	1.00	1.00	1.00
0.15	1.00	2.10	2.22
0.1	1.01	2.96	3.23
0.05	1.01	3.76	4.18
0	1.01	4.29	4.80

516 EMOD was designed primarily to model disease transmission and guide efforts toward  
 517 malaria eradication. Vector ecology in simplified larval habitat equations is incorporated into the  
 518 model with the primary goal of capturing transmission. Malaria studies that use EMOD adjust  
 519 mosquito lifecycle parameters to match real-world transmission metrics, including, but not  
 520 limited to, prevalence and incidence. In scenarios where field EIR data is readily available, the  
 521 modeling of vector ecology may even be bypassed entirely. In the former, parameter calibration  
 522 may not compensate for the simplified vector ecology representation in EMOD. In the latter, the  
 523 approach is highly dependent on the availability of field data. By incorporating hydrologic  
 524 modeling, we seek to improve the representation of larval habitats in EMOD as a first step  
 525 toward a more robust simulation of malaria transmission. In the future, other mosquito lifecycle  
 526 parameters that are seldom considered, such as mosquito emergence rates, should be calibrated.  
 527 This requires field data beyond prevalence and incidence, such as habitat productivity and adult  
 528 mosquito abundance.

#### 529 4.2. Insights Provided by Modeling on the Effect of Irrigation

530 By coupling hydrologic modeling with EMOD, we were able to investigate the effect of  
 531 irrigation on malaria by comparing two scenarios whereby irrigation was the only difference.  
 532 This allows us to isolate the effect of other environmental and social variables, such as  
 533 temperature, rainfall, topography, and demography, from the relationship between irrigation and  
 534 malaria transmission. The significance of our approach is that it supplements past field  
 535 comparative studies whereby the effect of irrigation could have been obscured by different field  
 536 settings (Ijumba & Lindsay, 2001). The approach also has the potential to explore hypothetical  
 537 scenarios to guide better decision-making in water resource management.

538 Our modeling elucidates a few ways in which irrigation affected malaria transmission  
 539 dynamics through larval habitats. First, all three habitat types increased in the dry season, while  
 540 temporary and semi-permanent habitats were converted to permanent habitats in the rainy  
 541 season. During the dry season, permanent habitats were the predominant habitat without  
 542 irrigation, but irrigation significantly increased the area of the temporary and semi-permanent  
 543 habitats (Figure 7a). The result was an increased diversity of the habitats which agrees with field  
 544 observations (Hawaria et al., 2019). On the other hand, permanent habitats became even more  
 545 dominant in the rainy season with irrigation. The change in relative abundance and stability of  
 546 the habitats may favor the growth and survival of one vector species over the other, shifting the

547 predominant vector species in the extreme case (Bamou et al., 2018; Chaves et al., 2021;  
548 Naranjo-Díaz et al., 2020).

549 Next, irrigation not only creates transmission all-year round but also intensifies the  
550 primary transmission period associated with the rainy season in terms of EIR and prevalence rate  
551 (Figure 8e-f). Studies have shown that irrigation can extend malaria transmission throughout the  
552 year due to water availability for breeding in the dry season (Kibret et al., 2014). Our results  
553 show that irrigation during the dry season can also increase the stability of the habitats in the  
554 rainy season by creating high soil moisture conditions favorable for ponding before the onset of  
555 the rainy season. As habitat stability is linked to adult vector density (Ndenga et al., 2011), this  
556 caused a more significant proliferation in adult vectors during the rainy season compared to *Non-*  
557 *Irrigation*. Besides a larger adult vector population in the rainy season, there could also be a  
558 carryover of parasites in the human population from the preceding dry season, resulting in a  
559 higher vector infection rate. This ripple effect has been observed in past studies investigating the  
560 link between malaria transmission season and preceding rainfall (Midekisa et al., 2015; Pascual  
561 et al., 2008). Our results suggest that irrigation can also produce the same cascading effect.

562 Thirdly, the modeling revealed that peak malaria transmission was shifted forward by  
563 around one month in the irrigation scenario (Figure 8e-f). Studies in East Africa have shown that  
564 rainfall significantly correlates with malaria transmission with a lag time of 1 to 2 months  
565 (Loevinsohn, 1994; Zhou et al., 2004). The lag can be attributed to the time for infiltration to  
566 occur, runoff to accumulate in low-lying areas, and the development time for parasite growth. In  
567 addition, past observations have proven that irrigation plays the same function as rainfall in  
568 providing larval habitats to support vector growth (Herrel et al., 2001; Ohta & Kaga, 2014).  
569 Hence, irrigation in the dry season in our study created a pseudo-early rainy season, which  
570 causes earlier onset of mosquito breeding and a peak in transmission.

571 Lastly, we demonstrated the effect of irrigation on the spatiotemporal distribution of  
572 malaria transmission by considering the heterogeneity of larval habitats (Figure 9). While past  
573 observations have told us that irrigation can increase the adult vector population (Demissew et  
574 al., 2020), it remains a challenge to predict where and when breeding will occur (Frake et al.,  
575 2020). Integrating local irrigation practices and environmental characteristics such as land use,  
576 topography, and soil properties, the model provided new insights into the breeding hotspots  
577 broken down into temporary, semi-permanent, and permanent habitat types. This information can  
578 help larval source management (LSM) as a supplementary vector control by prioritizing  
579 resources for operational planning. LSM is known to be efficient where habitats are findable, few  
580 and fixed (Djamouko-Djonkam et al., 2019; Stanton et al., 2021). Based on the results, we can  
581 identify the location of habitats, determine the period with manageable habitat abundance, and  
582 single out semi-permanent and permanent habitats for targeted larviciding. Comparing *Non-*  
583 *Irrigation* to *Irrigation* also allows us to distinguish habitats' hotspots induced by irrigation from  
584 those already present without irrigation. Other means, such as water resource management, can  
585 then be considered to control the former.

## 586 **5. Conclusion**

587 Malaria transmission is intrinsically related to larval habitats, which cannot be  
588 characterized by climate alone. By coupling a hydrologic model with an agent-based malaria  
589 model, the variability of larval habitats increased and resulted in significantly lower malaria  
590 transmission as opposed to modeling habitats based on a simplified function of climate factors.

591 We also demonstrated how habitat heterogeneity based on hydrologic processes could affect the  
592 spatiotemporal dynamics of malaria transmission.

593 The hydrology-integrated framework enabled us to investigate the effect of irrigation on  
594 malaria transmission through changes to larval habitats broken down into temporary, semi-  
595 permanent, and permanent types. The results indicated that all three habitat types increased in the  
596 dry season, while temporary and semi-permanent habitats were converted to permanent habitats  
597 during the rainy season. This influenced the transmission dynamics significantly as the  
598 transmission was sustained all-year round and intensified during the primary season. Lastly, the  
599 peak malaria transmission was found to be shifted forward by around one month. These insights  
600 can help guide malaria intervention strategies to mitigate the effect of irrigation.

601 The study presents a novel generalizable framework that simulates the spatiotemporal  
602 dynamics of malaria transmission under the influence of irrigation by integrating hydrologic  
603 modeling with an agent-based model. The framework is a first step toward developing tailor-  
604 made intervention strategies by simulating different water resource management practices. This  
605 is crucial to the continued implementation of irrigation schemes for food security while  
606 minimizing the impact on malaria transmission.

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## 618 **Conflict of Interest Statement**

619 The authors declare no conflicts of interest relevant to this study.

## 620 **Open Research**

621 The simulation softwares used in this research, ParFlow-CLM and EMOD, are available at  
 622 <https://doi.org/10.5281/zenodo.4816884> and <https://github.com/InstituteforDiseaseModeling/EMOD>  
 623 respectively. The precipitation records used as model input can be downloaded from the Data Portal  
 624 at Center for Hydrometeorology & Remote Sensing (Nguyen et al., 2019). Other climate input data  
 625 can be retrieved from Climate Data Store (Copernicus Climate Change Service, 2023). Surface  
 626 elevation data from can be purchased using the website <https://www.aw3d.jp/en/contactform/>. Land  
 627 cover data are available from [http://www.globallandcover.com/home\\_en.html](http://www.globallandcover.com/home_en.html) and soil data can be  
 628 downloaded from the SoilGrid database (<https://soilgrids.org/>). The larval habitat and malaria  
 629 incidence data used to calibrate EMOD are available from Zenodo  
 630 (<https://doi.org/10.5281/zenodo.7972323>).

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