CONTENTS

List of Tables . . . 1
List of Figures . . . 1
S1 Updated Synthetic Population Generation . . . 3
A Households . . . 5
B Workplaces . . . 5
C Schools . . . 5
D Serological Testing Model for CYD-TDV . . . 6
S2 Fitting with `AbcSmc` . . . 6
S3 Expanded Results . . . 9
References . . . 20

LIST OF TABLES

S1 Fitted epidemic model parameters . . . 7
S2 Epidemic Model fitting Metrics . . . 8

LIST OF FIGURES

S1 **Model Spatial Illustration**. Higher resolution versions of insets from Main Text Fig. 1. . . . 4
S2 **Single Intervention Annual & Cumulative Effectiveness.**. Medians (lines) and interquartile range (shaded ribbons) for all single intervention scenarios. Annotations are consistent with main text Fig. 2, with column faceting by vaccine mechanism (none versus CYD-TDV versus D70E). In addition to annual effectiveness (top row), this figure also shows cumulative effectiveness (bottom row), *i.e.* cases prevented since introduction of the intervention. . . . 9
S3 **Combined Intervention Interactions**. The interaction regions from main text Fig 4, shown as a trend line instead of a distance between two curves. The lines correspond to the shaded height shown in that figure (with additional rows in the faceting, for readability), while the ribbons here show the interquartile range for those lines. Where the line is above 0 (in the blue area) the interaction is typically amplifying, and where below 0 (in the red area), the interaction is typically interfering. . . . 10
S4 **Combined Intervention Annual & Cumulative Effectiveness**. The combined intervention medians (lines) from main text Fig 4, with interquartile range (ribbon). . . . 11
S5 **Staggered Intervention Starts**. Medians (line) and interquartile range (ribbon) for combined 75% TIRS and the D70E vaccine with a catch up campaign, faceted by the time delay before the second intervention is introduced. . . . 12
S6 **CYD-TDV Mosquito Population Sensitivity.**. Medians (line) and interquartile range (ribbon) for the combined intervention of 75% TIRS coverage and the CYD-TDV vaccine without a catch up campaign. The different mosquito population levels are a surrogate for force of infection (see Fig SS7). 12
S7 **Incidence vs. Relative Mosquito Population**. Annual infections and cases at equilibrium respond to changes in relative mosquito population, a surrogate for force of infection. The value at 1.0 corresponds to the population used for intervention analyses. The top panel shows infections that result in cases and the bottom panel shows all infections. In both panels, the dashed line shows the contribution from introduced infections. Note that cases begin to plateau at lower relative mosquito population; this is due to lower risk of disease for post-secondary infections. . . . 13
S8 **CYD-TDV Sensitivity to Mosquito Population with & without Serotesting**. Compares CYD-TDV effectiveness with and without conditioning vaccination on serostatus, across different mosquito population levels. Serological testing (as in the main text, with a 5% false positive rate, 20% false negative rate) prevents transient negative effectiveness in the low transmission setting, unconditional vaccination almost always outperforms testing in the long run. The exception is in the low transmission setting, in combination with TIRS: in that scenario, the natural force of infection has been driven so low that there are few seropositives in the age class targeted for vaccination, and hence limited benefit to CYD-TDV. In this instance, testing allows the intervention to benefit those few seropositives; without testing, the combination is less effective than just using TIRS alone. . . . 14

S9 **CYD-TDV Annual Effectiveness Across Testing Assumptions**. The black lines correspond to different testing performance scenario results, with no testing (red) and perfect testing (blue) reference lines repeated for each facet. The main text results focus on the bottom left scenario: 5% false seropositive rate, 20% false seronegative rate for testing. Interventions with testing generally have better early effects, but because the model interventions do not consider re-testing, eventually the assumed longer-term benefits do not appear for non-vaccinees. An intervention with high false negative rate tests fails to prevent about a third of the cases compared to a no testing approach. This provides additional support for the recent concerns about the cost-effectiveness of an intervention with limited benefit when negative predictive value is insufficient[1]. However, this gap is relative to total case count only; the difference framed in terms of costs may be smaller due to the potential for CYD-TDV to increase the incidence of severe disease. 15

S10 **CYD-TDV Cumulative Effectiveness Across Testing Assumptions**. Same results as Fig. SS9, but presented as cumulative effectiveness since starting the intervention. Cumulative effectiveness more clearly demonstrates the early performance benefit of testing (black), as it limits vaccine-accelerated cases. However, as most of those cases would have eventually happened in this high transmission setting, effectiveness is eventually penalized by the missed vaccination opportunities (relative to not requiring a positive serological test; red). In the transmission setting we considered, there is a crossover for low false seronegative rates (*i.e.*, black falls below red) between 10-15 years (for a program with catchup) after the intervention begins. For high false seronegative rates, testing and no testing are roughly comparable for the first 5 years, but after that unconditional vaccination is consistently superior at the population level. Because this effectiveness measure concerns total reported cases and does not directly account for case severity, this is not a recommendation for CYD-TDV without testing; rather, we are highlighting how much potential the intervention loses with poor test performance on false seronegative classification. A scenario with a perfect test (blue) is provided as a reference, but is less realistic than having an imperfect test. 16

S11 **75% TIRS & CYD-TDV Annual Effectiveness Across Testing Assumptions**. Same presentation as Fig. SS9, but with concurrent TIRS. Like the results for CYD-TDV vaccination only, the early performance of testing interventions is better, while the long-term performance of unconditional vaccination is superior. However, there is a generally a smaller long-term mismatch and a larger short-term benefit. Given the probable product lifetime for CYD-TDV, these much later trends are likely not practically important. 17

S12 **75% TIRS & CYD-TDV Cumulative Effectiveness Across Testing Assumptions**. Same results as Fig. SS11, but presented as cumulative effectiveness. Like the results for vaccination with CYD-TDV only, the combined interventions with unconditional vaccination eventually perform (at the population level) slightly better than approaches with test. However, the cross-over points are much later, from 20 to 30 years (sooner for high false negative rates and later for low ones) after initiating the intervention. 18

S13 **Sensitivity of Intervention Effectiveness to Conventional Vaccine Efficacy**. Similar to the D70E results presented in main text Fig. 4, though including conventional, durable vaccines with 50% and 90% efficacies (*i.e.*, D50E and D90E, respectively). Increasing efficacy of individual interventions increases overall effectiveness, particularly beyond 10-20 years. Combined interventions including a conventional vaccine always outperform the individual components, but at the 90% vaccine efficacy level, a high-coverage vaccination campaign may make vector control unnecessary for eliminating dengue. Though not examined here, control of *Ae. aegypti* may still be warranted to contain other diseases. While we regard 90% tetravalent efficacy irrespective of serostatus as optimistic, such vaccine efficacy is not impossible: durable, near perfect vaccine efficacy is observed for many viral pathogens. Should a very high efficacy vaccine become available, the choice between a one-time catch-up campaign and increased vector control will depend on other factors (*e.g.* vaccine availability, distribution logistics, presence of other *Aedes*-borne diseases). 19

S1. UPDATED SYNTHETIC POPULATION GENERATION

For this work, we have continued development of our agent based model of dengue transmission for Yucatán State, Mexico. The model is described in detail in [2] and [3]. We have updated our data sources and approach to generating the synthetic population used by the transmission model.

As an overview, our transmission model requires the following input:

- a list of locations representing households, schools, and workplaces;
- a list of mosquito movement probabilities between these locations; and
- a list of people, including household membership and school or workplace associations

In summary, our model explicitly represents 1,817,735 people, living in 376,400 households, some of whom go to either 3,124 schools or 114,713 workplaces. These individuals are aged 0 to 100 years old, and may be male or female, which is used when determining the potential for maternal-antibody-dependent enhancement when model infants are exposed to dengue. Age composition of households and employment and student status are according to distributions for each of the 106 municipalities in the State of Yucatán. Demographic and spatial distributions are based on real-world spatial-demographic data. The data sources we use include:

- Locality and municipality shapefiles
  - Source: Mexican population and housing census 2010, provided by Instituto Nacional de Estadística y Geografía (INEGI) via Sistema para la Consulta de Información Censal (SCINCE)
  - Description: INEGI has provided shapefiles of the 106 municipalities of Yucatan and the localities within them. For urban localities, polygons are provided; for rural localities, only points are provided.
  - Usage: Random allocation of schools coordinates – localities and municipalities of schools that cannot be geocoded are matched with these shapefiles.
  - Additional references: Download links (in .exe) and more information.
- Nighttime light raster - VIIRS Day/Night Band Nighttime Lights
  - Source: Earth Observation Group, NOAA [4]
  - Description: Annual composites of the Visible Infrared Imaging Radiometer Suite (VIIRS) Day/Night Band (DNB) radiance in 2015. Data provider has removed the outliers, screened out the ephemeral lights and set the background (non-lights) to zero.
  - Usage: As a proxy for population and building density.
- Household census data
  - Source: Integrated Public Use Microdata Series, International (IPUMS) [5]
  - Description: 5% sample of Yucatan households, stratified by municipality
  - Usage: Determining household size and composition (age, sex, and daytime activity)
- Workplace location data
  - Source: DENUE [6]
  - Description: Data table containing names, addresses, localities and municipalities of 114,713 non-school workplaces
  - Usage: To generate workplace coordinates
- School location data
  - Source: SEGEY [7]
  - Description: Data table containing names, addresses, localities and municipalities of 3,290 schools
  - Usage: To generate schools coordinates

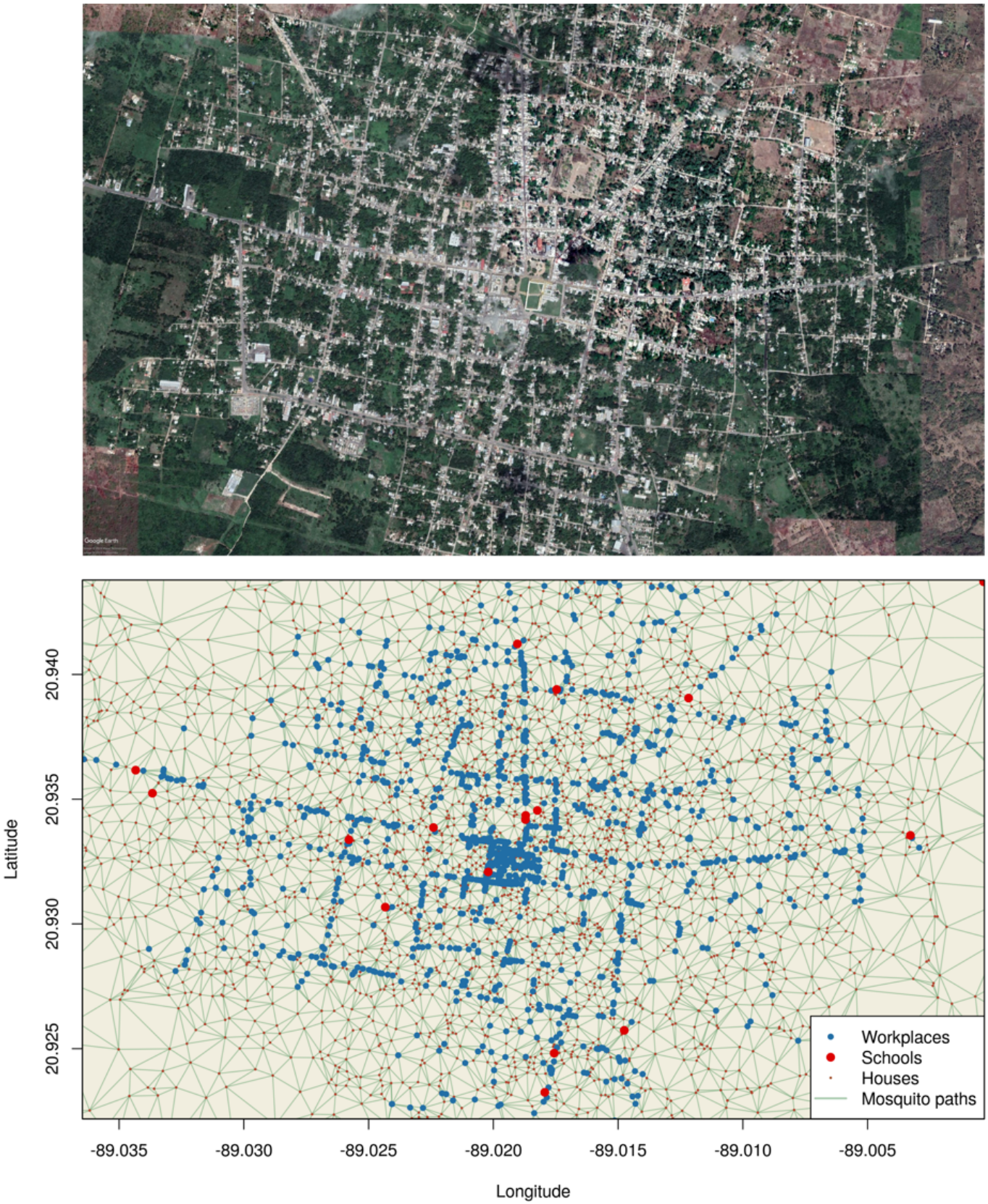


Figure S1. **Model Spatial Illustration**. Higher resolution versions of insets from Main Text Fig. 1.

A. Households

We use the same algorithm for placing households as in [2, 3], but with updated shapefile and remote sensing data. Households for each of the 106 municipalities in Yucatán are sampled from IPUMS microcensus data. The number of households sampled for each municipality is based on the expected household size, and the 2010 Mexico census [8]. Households are placed within municipality boundaries as defined by [8], in pixels (resolution of $\approx$ 500m) proportional to the light output recorded by NOAA/VIIRS nighttime satellite imagery[4]. Within pixels, households are located uniformly randomly. The satellite images are composite images taken on nights with no moonlight. The composite images do not contain clouds, and in this updated data from NOAA, background noise (*e.g.* reflected star light) has been removed.

B. Workplaces

Our workplace placement model previously Of the 117728 registered business entries, 9619 of them have non-unique coordinates (in latitude and longitude). We calculated the 5th percentile of longitudinal and latitudinal difference among businesses in Merida, which are 0.001° and 0.0006° respectively. Non-unique coordinates were randomly jittered by these values.

The work place size data is provided in size categories, but we need specific sizes for our algorithm. To get sizes, we fit a power-law distribution model to the category data, then drew from that distribution to obtain specific sizes.

Although schools are included among the workplaces provided by DENUE, we found that the school data provided by SEGEY was more accurate and complete. We therefore omitted schools from the DENUE data and placed them as described in the section below. Schools are also workplaces, however, and thus we determined the number of employees by first assigning students to the closest school, and then setting the expected number of employees to twice the student:teacher ratio for Mexico [9]. We doubled the student-teacher ratio in order to account for support staff, consistent with our observations when visiting schools in Yucatán.

We use a censored gravity model for assigning people to workplaces. If the IPUMS data for a given person indicates that they are employed, we sample an employer from the 1000 workplaces closest to their house with probability proportional to workplace size over Euclidean distance to the workplace squared.

C. Schools

Our school placement model previously relied on postal code data. In rural areas we found this approach sometimes lead to unrealistic placement, with schools placed several kilometers outside of the rural villages they actually exist within. We confirmed that the postal code data was unreliable by finding schools, in person, in four rural villages that supposedly did not have schools. By using Google Maps and Google Street View, we further confirmed that even very small and remote villages have official schools, but these schools often do not have official addresses. We have thus completely revised our algorithm for locating schools.

Our model does not distinguish between types of schools (*e.g.* primary and secondary), but [7] lists them as distinct schools even if they operate in the same building. We consolidated entries with identical name, address, locality and municipality into one entry. The number of students in these consolidated entries are the sum of all duplicated entries. This reduced the number of school locations from 3290 to 3124. The geographic coordinates for the 3124 schools were determined using following steps:

1. We used the Google Maps Geocoding API to convert the school addresses to coordinates. Many, but not all, of the coordinates returned were acceptable. The results that satisfied the following rules were accepted:
    - The coordinate (from Google) is less than 5km from its nominal locality (*i.e.* town, village, or city) and municipality (from SCINCE shapefiles). Some school and street names match different localities than the school is actually in.
    - The coordinate is unique. When Google does not know where an a street address is, it sometimes chooses the center of a locality. While this might be an acceptable approximation if a village only has one school, we did not permit schools with distinct names and addresses to be located at the same point.
2. Based on these rules, we accepted the Google's coordinate for 1576 school entries.
3. For the rest of the 1548 schools, we imputed their coordinates. For each school, we matched the locality and municipality with the SCINCE shapefiles.

4. There were 1495 schools with matching polygons (urban) or points (rural), 44 of which had more than one match. We used the following steps to place these:
    - For each urban polygon, all pixels within the polygon were selected.
    - For each rural points, all pixels (a) within the 5km distance from the point, (b) within the municipality, and (c) not belong to an urban polygon were selected.
    - Randomly sample one out of the selected pixels, with probability of selection weighted by the pixels' nighttime light value.
    - Sample coordinates uniformly within the pixel, and assign them to the school.
5. For the remaining 53 schools that had municipality information, but did not have a locality that could be matched to the SCINCE shapefiles, we assigned locations according to the following steps:
    - Select all pixels within the municipality's polygons that do not belong to an urban polygon (i.e. assuming the school is not in urban area).
    - Randomly sample one out of all selected pixels, with probability of selection weighted by the pixels' nighttime light value.
    - Sample coordinates uniformly within the pixel, and assign them to the school.

People age 5–11 years old or designated as students by IPUMS are assigned to the schools that are closest to their houses.

D. Serological Testing Model for CYD-TDV

Current guidance for CYD-TDV is that the vaccine should only be administered to seropositive individuals, but an appropriate rapid diagnostic test is not currently available. As a rapid diagnostic test does not yet exist, we judge that to be practical to develop and acceptable to use, the test will prioritize specificity over sensitivity. Thus we assume for main text results that the test has 5% probability of misclassifying a seronegative individual as seropositive (*i.e.*, 95% specific) and has a 20% probability of misclassifying a seropositive individual as seronegative (80% sensitive). In Figs. S9-, we show results for alternative test performance assumptions, as well as vaccinating without testing.

Individuals in eligible age classes are randomly selected to be considered for vaccination depending on coverage (generally assumed to be 80%). Vaccination with CYD-TDV in our simulation then depends on the testing model used for that replicate:

- for the no testing model, all individuals randomized for coverage receive the vaccine.
- for the perfect testing model, after individuals are randomized for coverage, they only receive the vaccine if they are seropositive, *i.e.* they have been previously infected (including if they are currently infected)
- for the imperfect testing model, after individuals are randomized for coverage, serostatus is sometimes incorrectly determined by the test. Observed seropositives receive the vaccine. If they are seronegative, they may be observed as seropositive according to the false positive rate, and likewise if they are seropositive they may be observed as seronegative according to the false negative rate. Whether correctly determined or misclassified, individuals are vaccinated (or not) according to their observed serostatus.

  We considered imperfect tests with different misclassification properties, mixing higher performance (5% chance of misclassification) vs lower performance (20% chance of misclassification) assumptions for both aspects of testing performance (false positive and false negative rates).

S2. FITTING WITH `ABCSMC`

Refitting was necessary because of changes to the synthetic population as described above. As these changes to geography seemed unlikely to significantly impact model fit, we resumed fitting from the estimates in [3], using [10] to compute 5 more sets of 10k particles each. From each set, the top 500 were chosen for the predictive prior. The final posterior was the 1k best particles of the 50k simulated; these are the 1000 parameter combinations that were used when simulating results.

Parameter	Sampled Prior	Modeled Prior		Posterior	
		Mean	Range	Median	95% IR
RF_m	$\mathcal{N}$(-2.944439, 1.4)	0.0595	[0.01, 1]	0.0283	[0.01,0.486]
$UR_{m,95}$	$\mathcal{N}$(-0.5, 1)	0.384	[0.01, 1]	0.0112	[0.01,0.114]
RF_s	$\mathcal{N}$(-1.098612, 0.8)	0.265	[0.02, 1]	0.167	[0.02,0.999]
SP	$\mathcal{N}$(0.8472979, 0.7)	0.7	[0, 1]	0.399	[0.0804,0.995]
SS	$\mathcal{N}$(-2.197225, 2.25)	0.1	[0, 1]	0.009 57	[8.94e-06,0.277]
$PSSR$	$\mathcal{N}$(0, 1)	0.5	[0, 1]	0.398	[7.46e-07,1]
λ_E	$\mathcal{N}$(-4.5, 1.5)	0.275	[0, 25]	2.26	[0.00302,22.4]
M_{peak}	$\mathcal{N}$(0, 0.7)	60.5	[1, 120]	40.8	[28,52.8]

Table S1. Prior distributions (sampled and modeled) and posterior medians and 95% interquantile ranges (IR) for fitted epidemic model parameters. Standard logistic transformations (*i.e.*, $k = 1, x_0 = 0$) were used to convert sampled parameter values into model parameter values based on the ranges specified. RF_m is the reported fraction for mild disease; $UR_{m,95}$ is the fraction by which mild cases are under-reported pre-1995; RF_s is the reported fraction for severe disease; SP is the reference (secondary infection with DENV 1) pathogenicity; SS is reference (secondary case) probability of severe disease; $PSSR$ is the relative-risk of severe disease in primary cases; λ_E is the introduction rate (number of exposures per serotype per day, for the entire modeled population); M_{peak} is the mean number of mosquitoes per location, on the day when mosquito populations are largest.

In previous work, the proposal mechanism was described as using the between parameter covariance for noising in addition to within parameter variance when recommending new parameter combinations during fitting. The between parameter portion was not incorporated correctly, leading to slower convergence rates. We corrected the implementation of this feature for this round of fitting. Based on the difference between metric fits between these results and the previous fit [3], the proposal error does not seem to have had a substantial effect on the final parameters.

Metric	Observed	Posterior		
		Mean	Median	95% IR
mean	101	116	99.3	[15, 295]
minimum	0	0.0424	0	[0, 0.547]
25^{th} percentile	2.73	7.58	5.15	[0, 28.3]
median	38	44.8	36.4	[0.048, 141]
75^{th} percentile	129	128	107	[8.11, 365]
maximum	464	754	625	[98, 2130]
SD	140	182	146	[24.2, 523]
skewness	1.38	2.09	2.08	[1.36, 2.91]
median-crossing rate	0.25	0.265	0.278	[0.167, 0.333]
1987 seroprevalence, 8–14 yo	0.6	0.701	0.702	[0.503, 0.886]
pre-1995 severe proportion	0.000 697	0.103	0.0898	[0.0246, 0.247]
modern severe proportion	0.29	0.147	0.131	[0.0376, 0.327]
2014 seroprevalence, 0–4 yo	0.278	0.239	0.233	[0.0673, 0.445]
ibid., 5–9 yo	0.49	0.432	0.438	[0.304, 0.537]
ibid., 10–14 yo	0.616	0.561	0.571	[0.375, 0.685]
ibid., 15–19 yo	0.727	0.665	0.679	[0.499, 0.762]
ibid., 20–29 yo	0.741	0.777	0.786	[0.645, 0.852]
ibid., 30–39 yo	0.708	0.903	0.91	[0.81, 0.949]
ibid., 40–49 yo	0.808	0.957	0.963	[0.865, 0.991]
ibid., 50–59 yo	0.742	0.981	0.986	[0.914, 0.998]
ibid., 60+ yo	0.828	0.995	0.998	[0.971, 1]

Table S2. Observed data and model fitting posterior means, medians, and 95% interquantile range (IR) for epidemic model metrics. Posterior values are for simulations on the Yucatán population after averaging across 10 realizations for each of the 1000 parameter combinations that resulted from the fitting procedure. The 1987 seroprevalence survey concerned only 8–14 year old Mérida residents, which were explicitly subset from the simulated Yucatán population. The Mérida population was defined as people whose household is within the bounding box constrained by latitudes 20.847583 and 21.076652, and longitudes -89.752178 and -89.504299.

S3. EXPANDED RESULTS

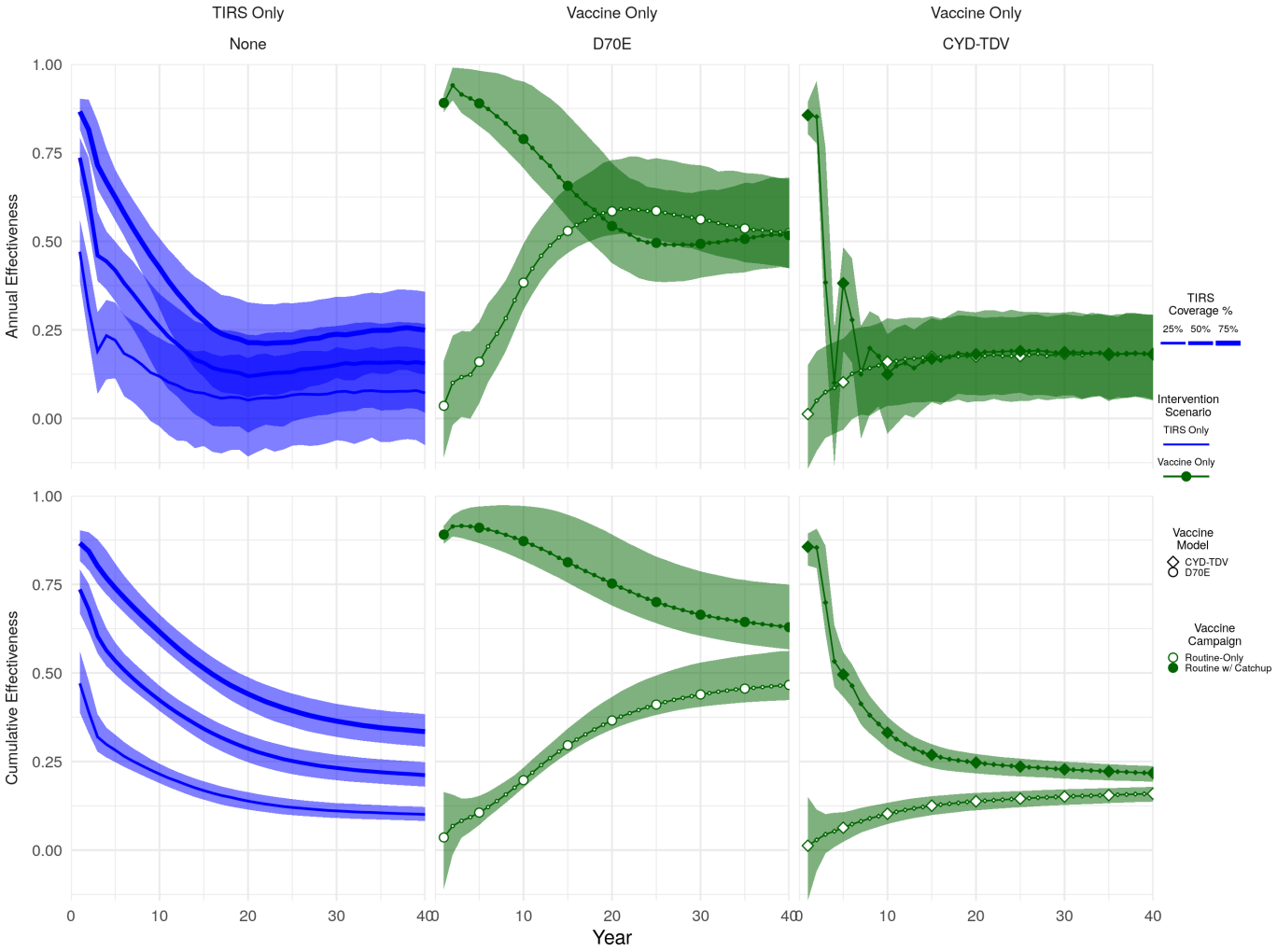
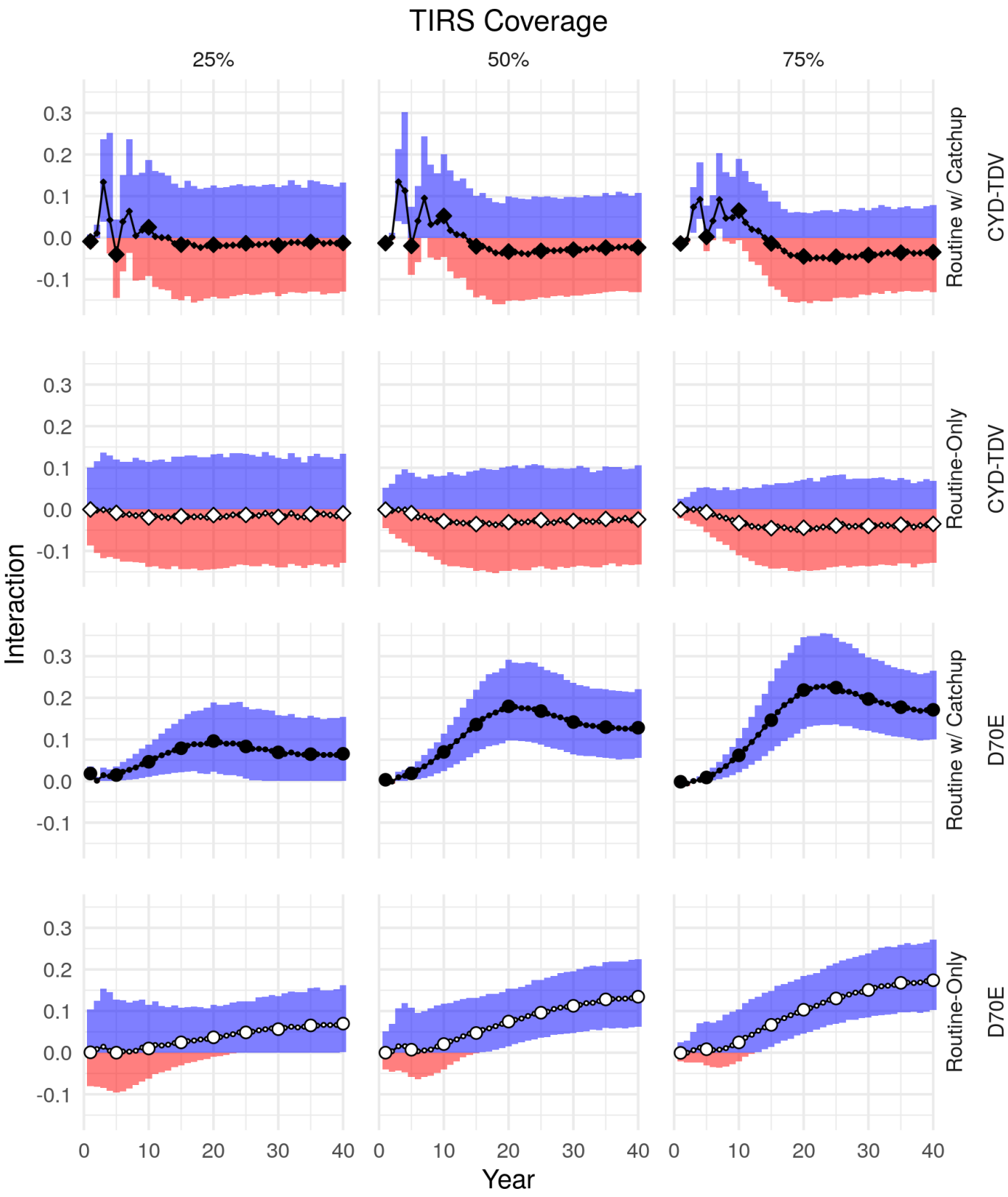


Figure S2. **Single Intervention Annual & Cumulative Effectiveness.**. Medians (lines) and interquartile range (shaded ribbons) for all single intervention scenarios. Annotations are consistent with main text Fig. 2, with column faceting by vaccine mechanism (none versus CYD-TDV versus D70E). In addition to annual effectiveness (top row), this figure also shows cumulative effectiveness (bottom row), *i.e.* cases prevented since introduction of the intervention.



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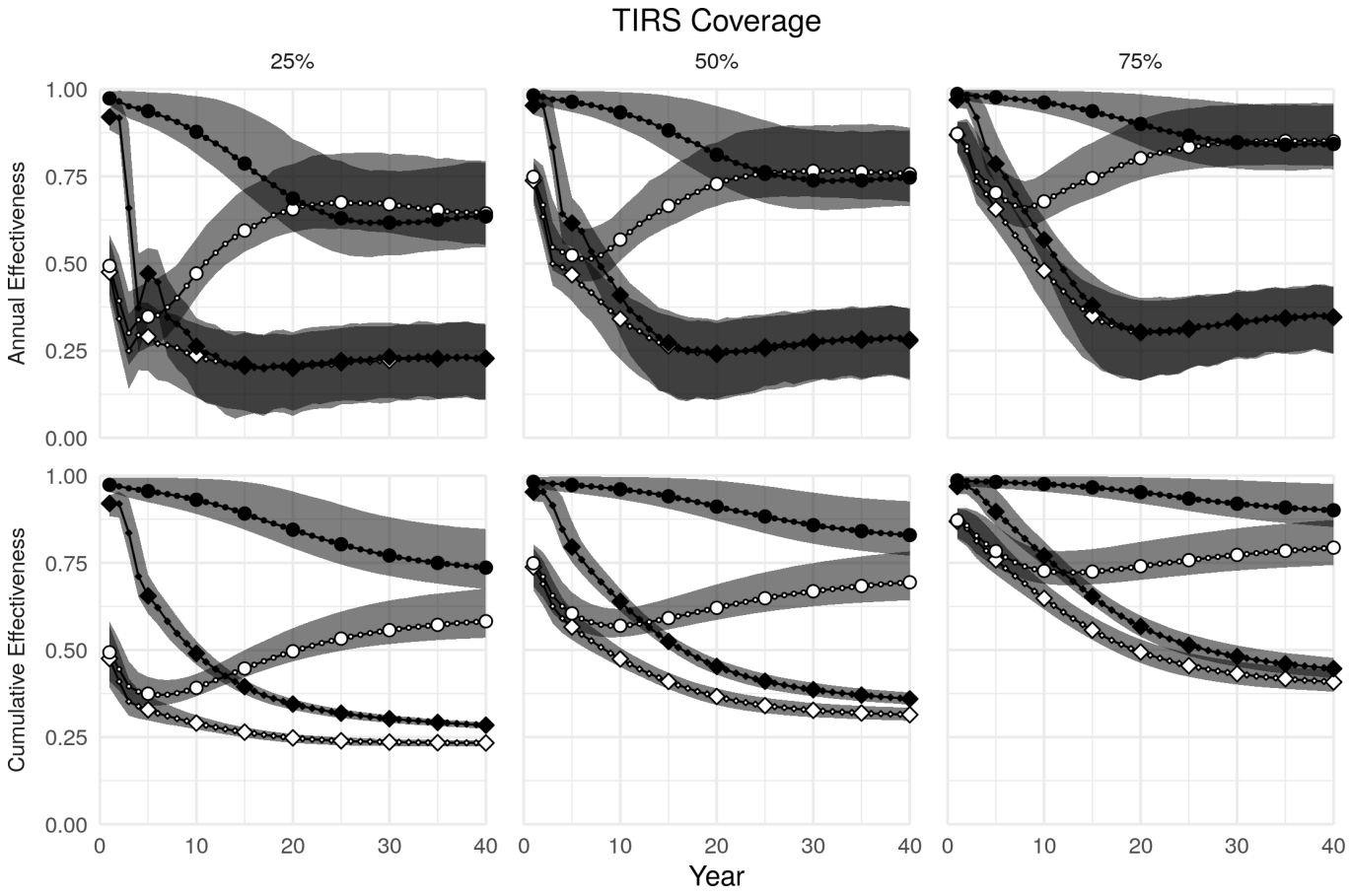

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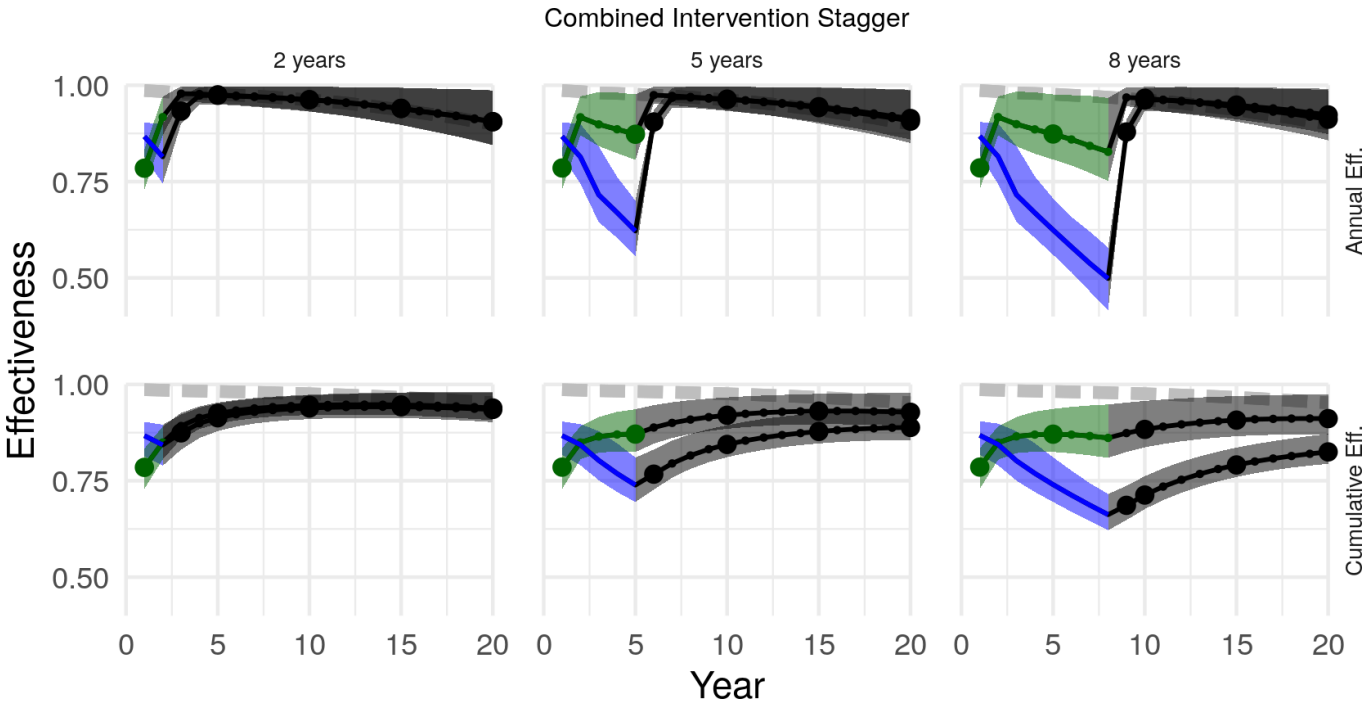

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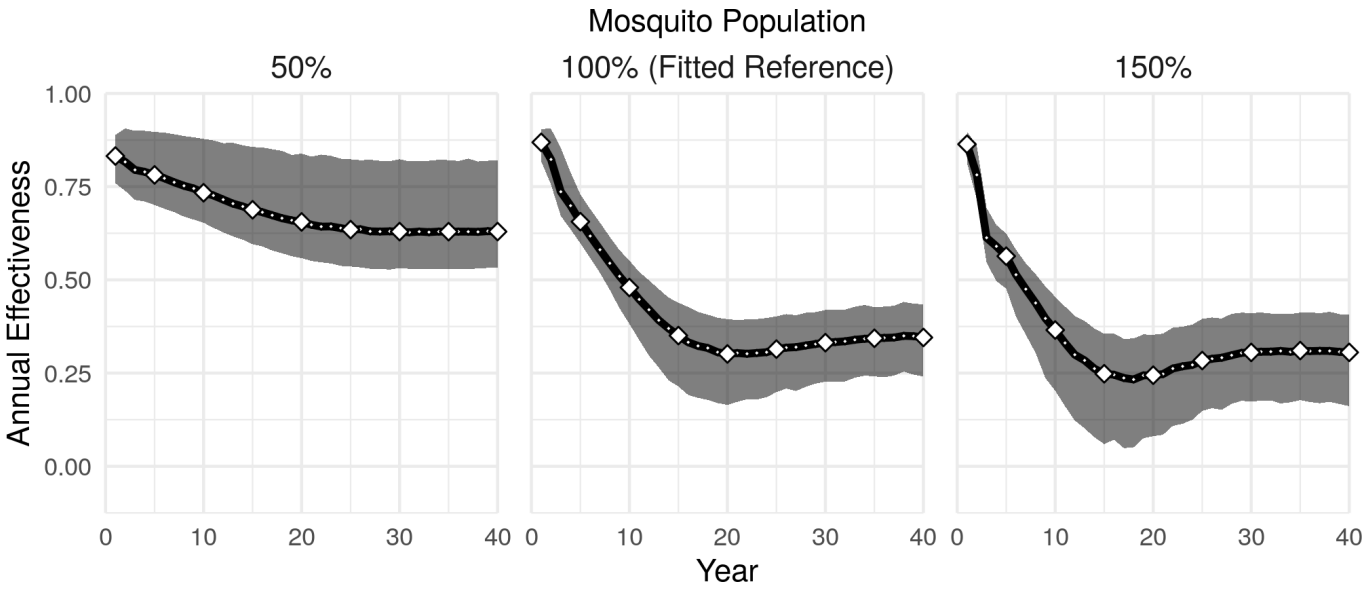
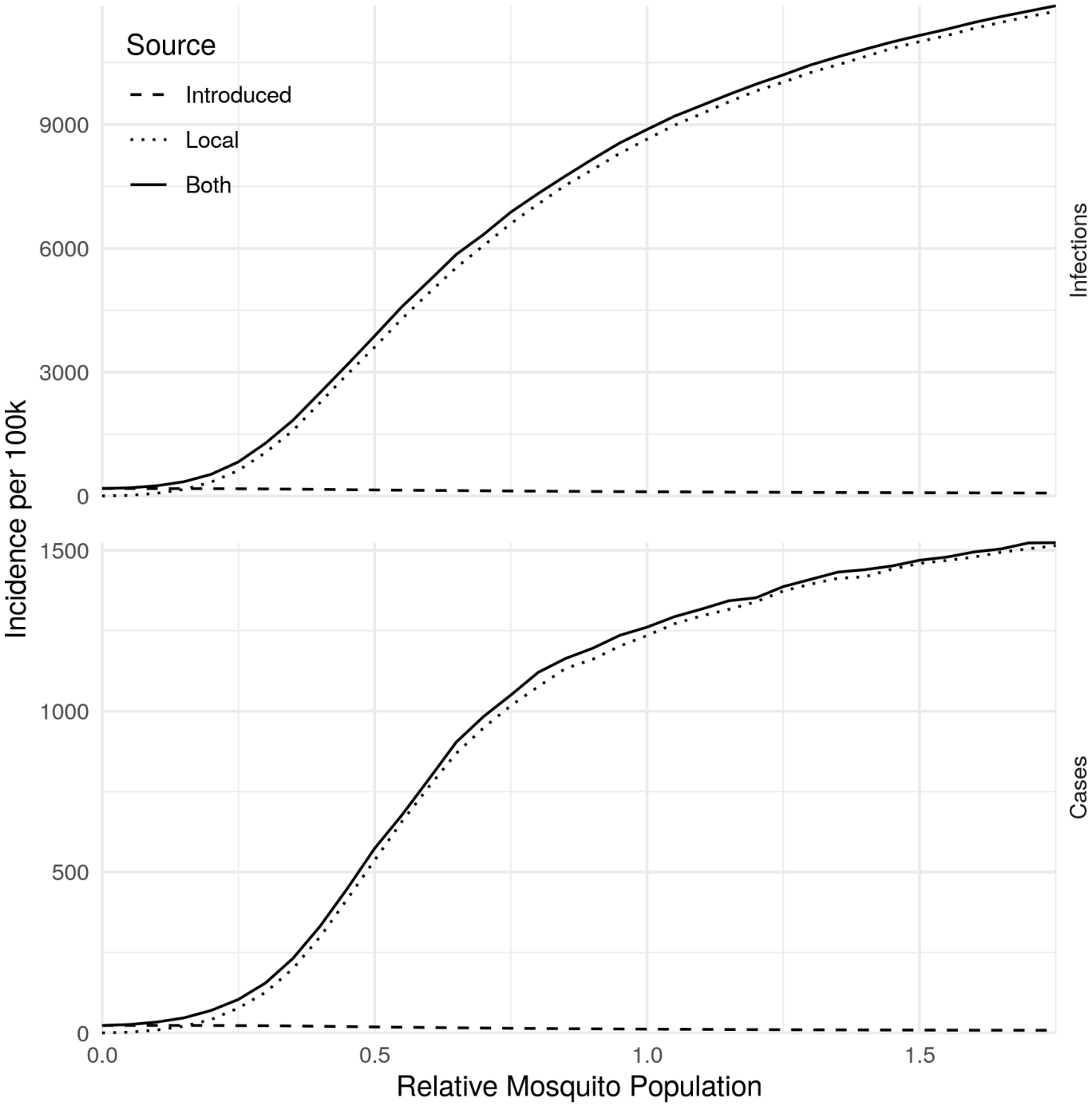


Figure S6. **CYD-TDV Mosquito Population Sensitivity.**. Medians (line) and interquartile range (ribbon) for the combined intervention of 75% TIRS coverage and the CYD-TDV vaccine without a catch up campaign. The different mosquito population levels are a surrogate for force of infection (see Fig SS7).



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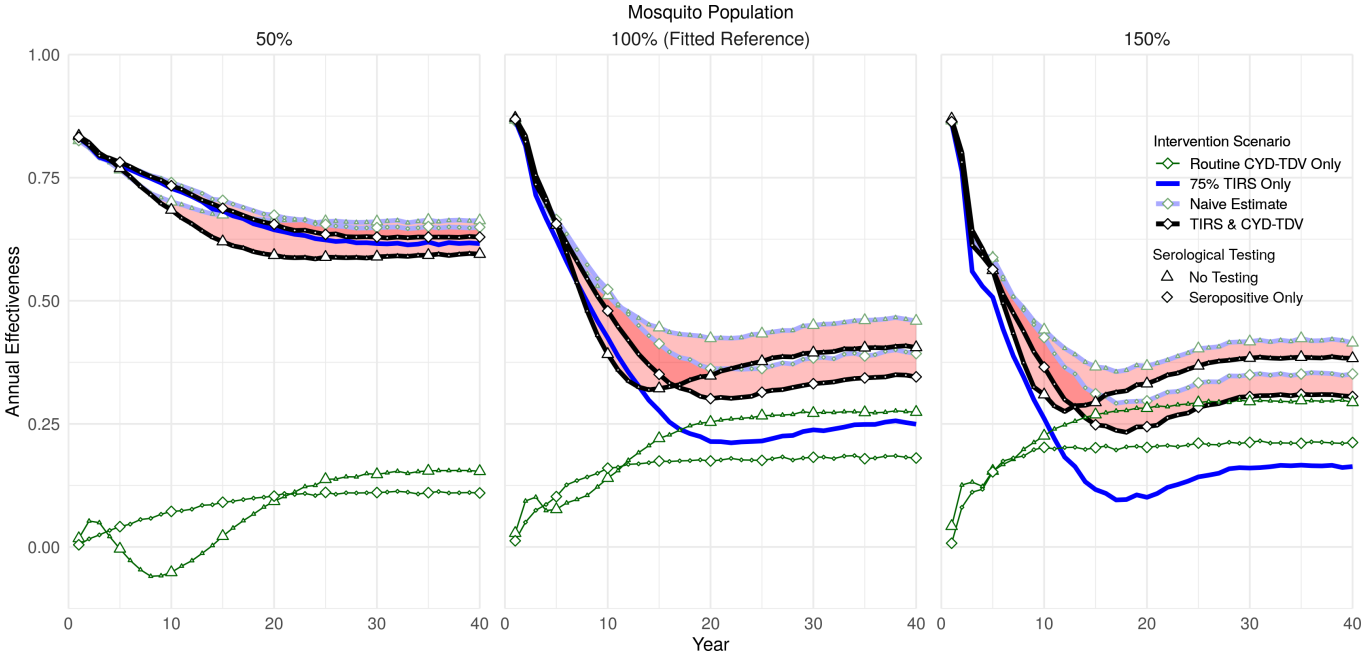

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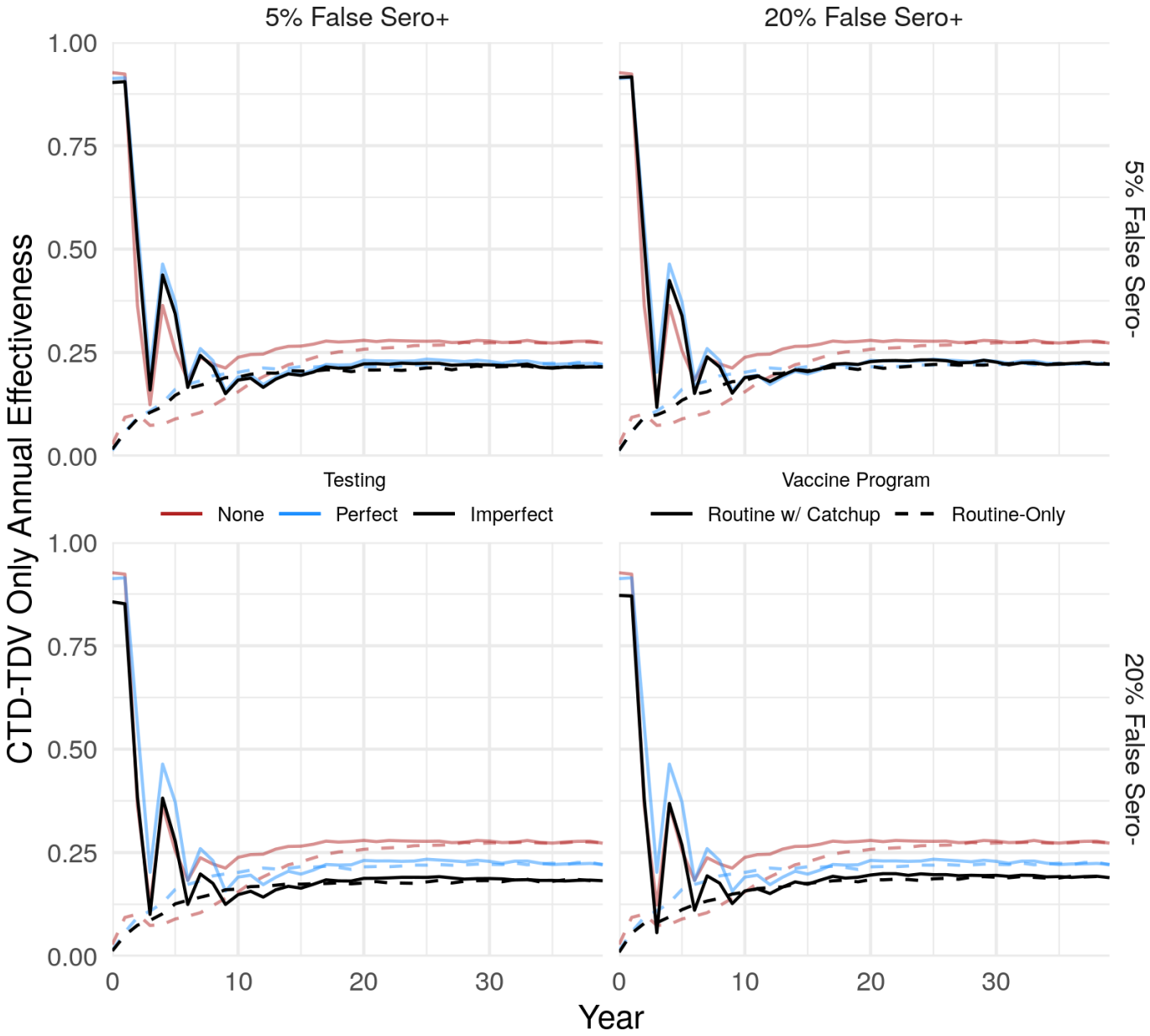

Figure S9. **CYD-TDV Annual Effectiveness Across Testing Assumptions**. The black lines correspond to different testing performance scenario results, with no testing (red) and perfect testing (blue) reference lines repeated for each facet. The main text results focus on the bottom left scenario: 5% false seropositive rate, 20% false seronegative rate for testing. Interventions with testing generally have better early effects, but because the model interventions do not consider re-testing, eventually the assumed longer-term benefits do not appear for non-vaccinees. An intervention with high false negative rate tests fails to prevent about a third of the cases compared to a no testing approach. This provides additional support for the recent concerns about the cost-effectiveness of an intervention with limited benefit when negative predictive value is insufficient[1]. However, this gap is relative to total case count only; the difference framed in terms of costs may be smaller due to the potential for CYD-TDV to increase the incidence of severe disease.

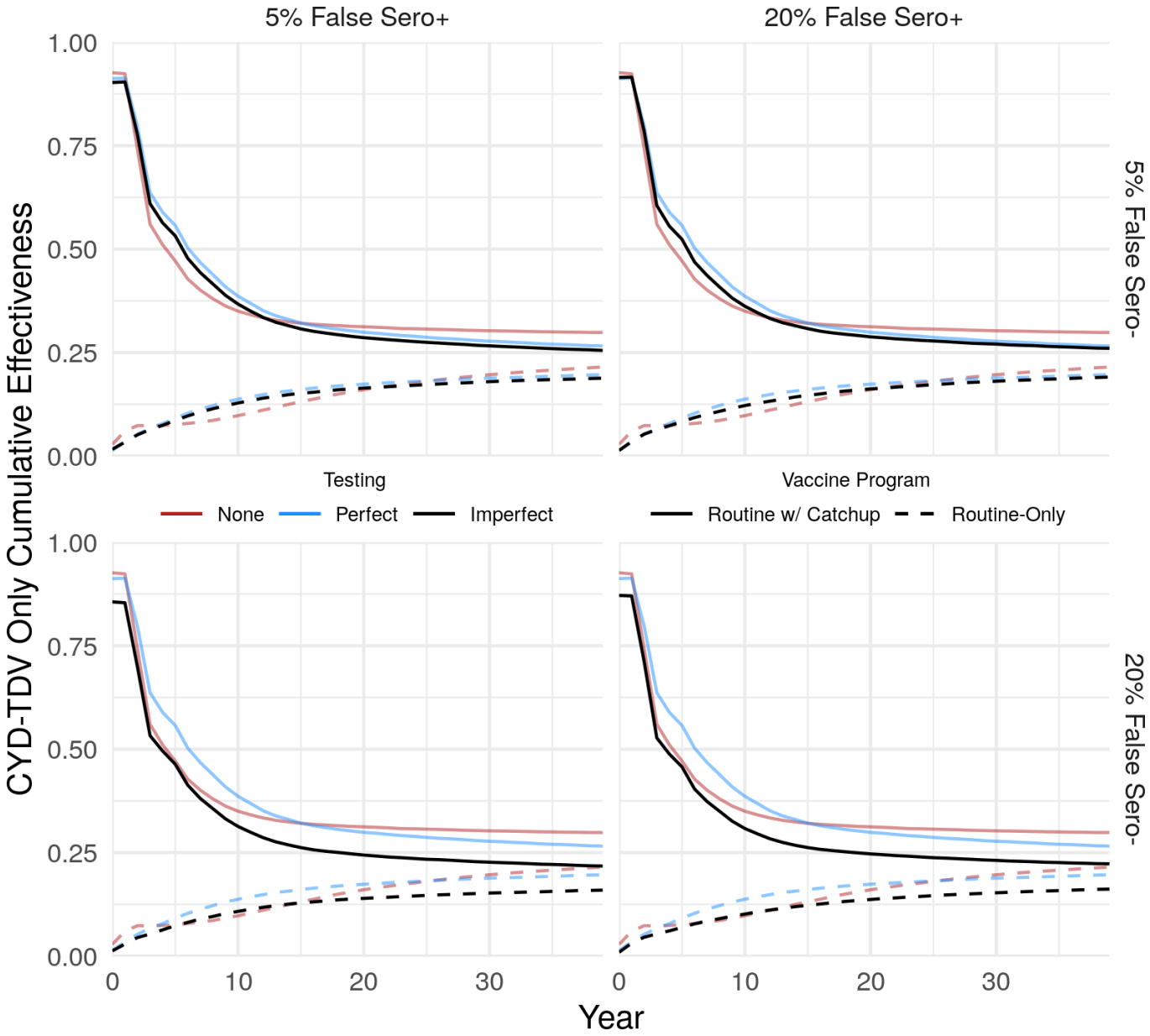

Figure S10. **CYD-TDV Cumulative Effectiveness Across Testing Assumptions**. Same results as Fig. SS9, but presented as cumulative effectiveness since starting the intervention. Cumulative effectiveness more clearly demonstrates the early performance benefit of testing (black), as it limits vaccine-accelerated cases. However, as most of those cases would have eventually happened in this high transmission setting, effectiveness is eventually penalized by the missed vaccination opportunities (relative to not requiring a positive serological test; red). In the transmission setting we considered, there is a crossover for low false seronegative rates (*i.e.*, black falls below red) between 10-15 years (for a program with catchup) after the intervention begins. For high false seronegative rates, testing and no testing are roughly comparable for the first 5 years, but after that unconditional vaccination is consistently superior at the population level. Because this effectiveness measure concerns total reported cases and does not directly account for case severity, this is not a recommendation for CYD-TDV without testing; rather, we are highlighting how much potential the intervention loses with poor test performance on false seronegative classification. A scenario with a perfect test (blue) is provided as a reference, but is less realistic than having an imperfect test.

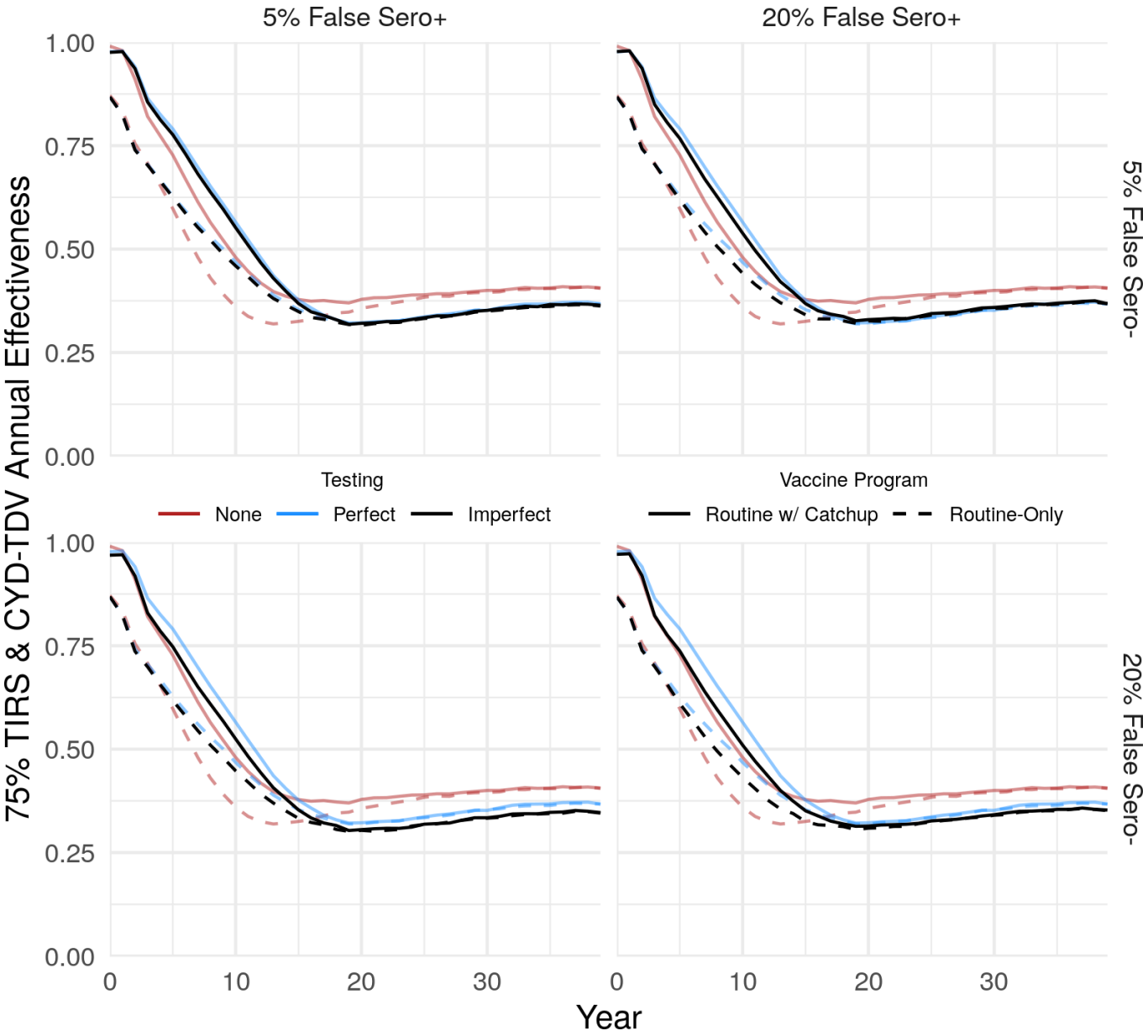

Figure S11. **75% TIRS & CYD-TDV Annual Effectiveness Across Testing Assumptions**. Same presentation as Fig. SS9, but with concurrent TIRS. Like the results for CYD-TDV vaccination only, the early performance of testing interventions is better, while the long-term performance of unconditional vaccination is superior. However, there is a generally a smaller long-term mismatch and a larger short-term benefit. Given the probable product lifetime for CYD-TDV, these much later trends are likely not practically important.

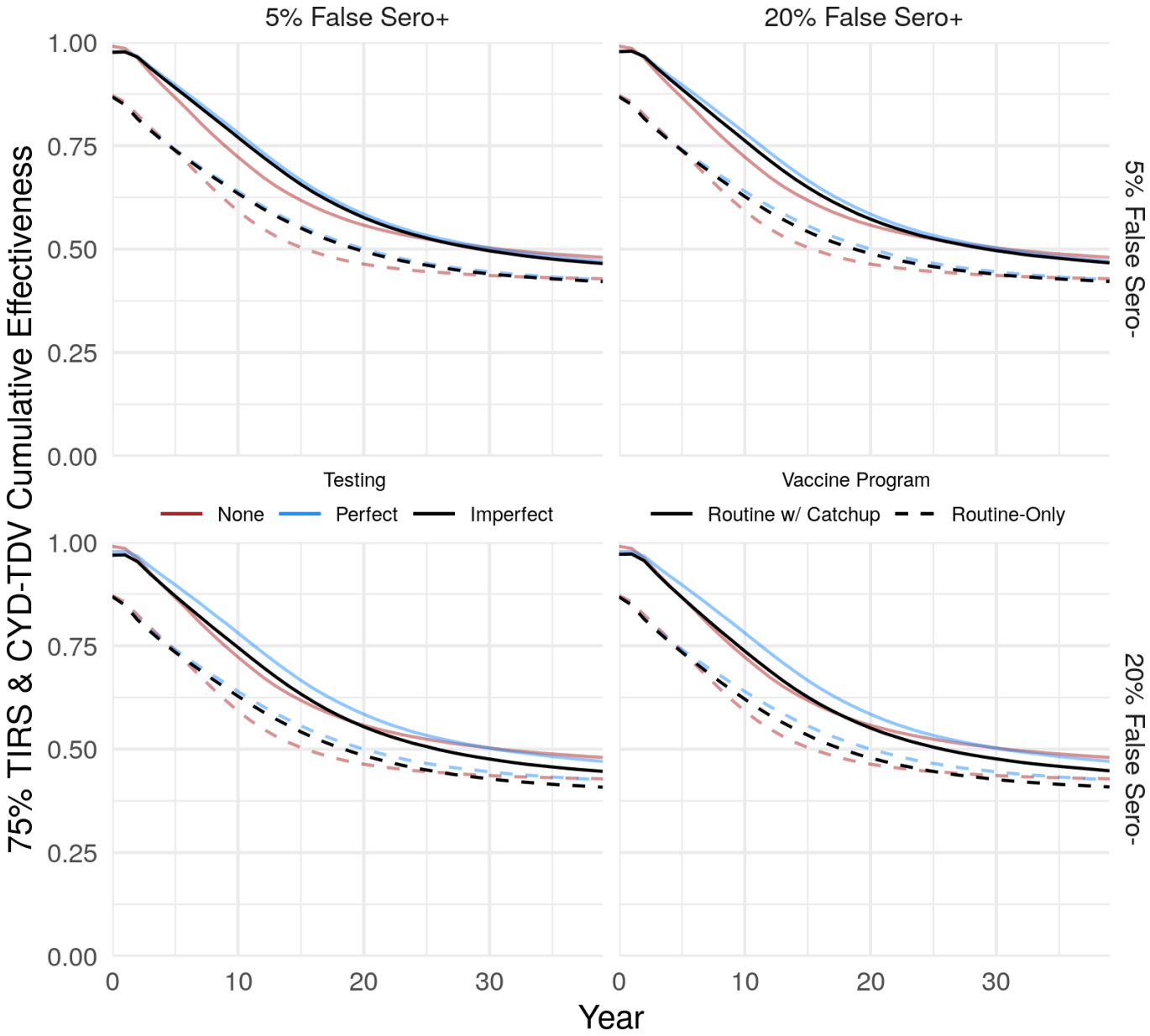

Figure S12. **75% TIRS & CYD-TDV Cumulative Effectiveness Across Testing Assumptions**. Same results as Fig. SS11, but presented as cumulative effectiveness. Like the results for vaccination with CYD-TDV only, the combined interventions with unconditional vaccination eventually perform (at the population level) slightly better than approaches with test. However, the cross-over points are much later, from 20 to 30 years (sooner for high false negative rates and later for low ones) after initiating the intervention.

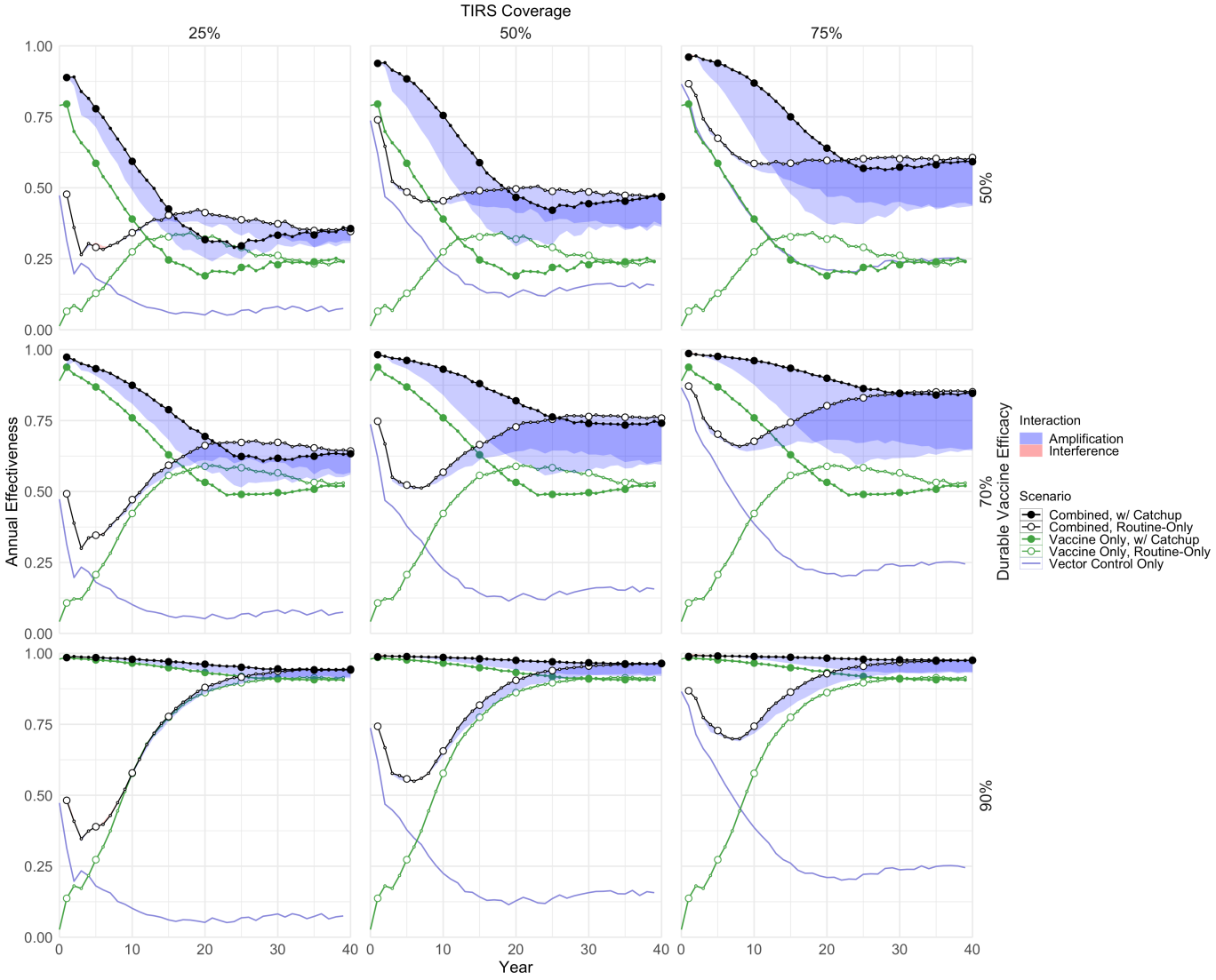

Figure S13. **Sensitivity of Intervention Effectiveness to Conventional Vaccine Efficacy**. Similar to the D70E results presented in main text Fig. 4, though including conventional, durable vaccines with 50% and 90% efficacies (*i.e.*, D50E and D90E, respectively). Increasing efficacy of individual interventions increases overall effectiveness, particularly beyond 10-20 years. Combined interventions including a conventional vaccine always outperform the individual components, but at the 90% vaccine efficacy level, a high-coverage vaccination campaign may make vector control unnecessary for eliminating dengue. Though not examined here, control of *Ae. aegypti* may still be warranted to contain other diseases. While we regard 90% tetravalent efficacy irrespective of serostatus as optimistic, such vaccine efficacy is not impossible: durable, near perfect vaccine efficacy is observed for many viral pathogens. Should a very high efficacy vaccine become available, the choice between a one-time catch-up campaign and increased vector control will depend on other factors (*e.g.* vaccine availability, distribution logistics, presence of other *Aedes*-borne diseases).

[1] Flasche S, Smith PG (2019) Sensitivity and negative predictive value for a rapid dengue test. *The Lancet Infectious Diseases* 19(5):465–466.
[2] Hladish TJ, et al. (2016) Projected impact of dengue vaccination in Yucatán, Mexico. *PLoS Neglected Tropical Diseases* 10(5):e0004661.
[3] Hladish TJ, et al. (2018) Forecasting the effectiveness of indoor residual spraying for reducing dengue burden. *PLoS Neglected Tropical Diseases* 12(6):e0006570.
[4] Earth Observation Group, NOAA National Geophysical Data Center (2018) VIIRS DNB Cloud Free Composites (`http://ngdc.noaa.gov/eog/viirs/download_monthly.html`).
[5] Minnesota Population Center (2014) Integrated Public Use Microdata Series, International: Version 6.3 [machine-readable database] (`https://international.ipums.org/international/`).
[6] Directorio Estadístico Nacional de Unidades Económicas (DENUE) (2018) (`http://www3.inegi.org.mx/sistemas/mapa/denue/default.aspx`).
[7] Secretaría de Educación de Yucatán (SEGEY) (2018) (`http://www.educacion.yucatan.gob.mx/`).
[8] Instituto Nacional de Estadística y Geographía (2015) Banco de información (`http://www3.inegi.org.mx/sistemas/biinegi/`).
[9] World Bank (2015) Pupil-teacher ratio, primary (`http://data.worldbank.org/indicator/SE.PRM.ENRL.TC.ZS`).
[10] Hladish TJ (2019) Sequential Monte Carlo approximate Bayesian computation with partial least squares parameter estimator (AbcSmc) (`https://github.com/tjhladish/abcsmc/`).