

Pandemic Influenza Modeling in West Texas

A "Ready-to-Deploy" Disease Model to Support Public Health Pandemic Planning in West Texas

Avery Conrad, MPH

Texas Department of State Health Services, Public Health Region 9/10



TEXAS
Health and Human
Services

Texas Department of State
Health Services

dshs.texas.gov

Introduction

When pandemics occur, public health jurisdictions need fast, reliable answers: Which hospitals are at risk of being overwhelmed? Will masking or vaccination make a meaningful difference? West Texas presents unique challenges, with large rural distances and varied healthcare capacity across the region.

This project built a "ready-to-deploy" disease model tailored to Public Health Region 9/10 that estimates hospital surge risk under different pandemic scenarios and connects directly to existing surveillance data.

Objectives

- Identify which hospitals and subregions face the greatest surge risk before a pandemic peaks
- Model the impact of interventions (masking, vaccination, antivirals) on hospital demand to guide decision-making
- Connect to near real-time emergency department data (ESSENCE) so outputs reflect current conditions, not just assumptions
- Serve as a reusable, adaptable tool ready to deploy for future respiratory pandemic threats in West Texas

Methods

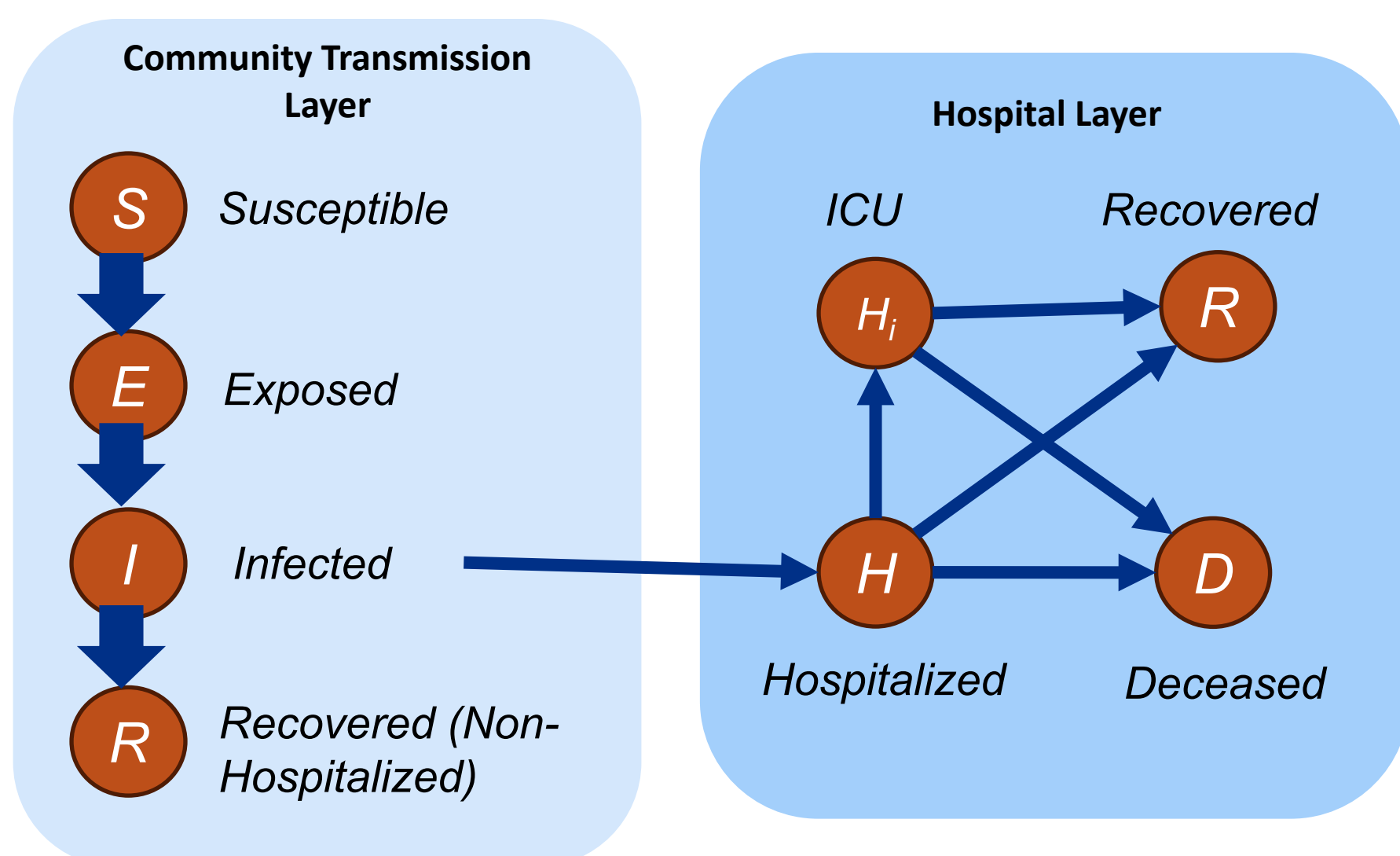


Figure 1. SIERD + H Model shows the flow of disease states between compartments. Hospitalization is modeled as a subset of infectious cases, with escalation from non-ICU to ICU and recovery or death as the outcome.

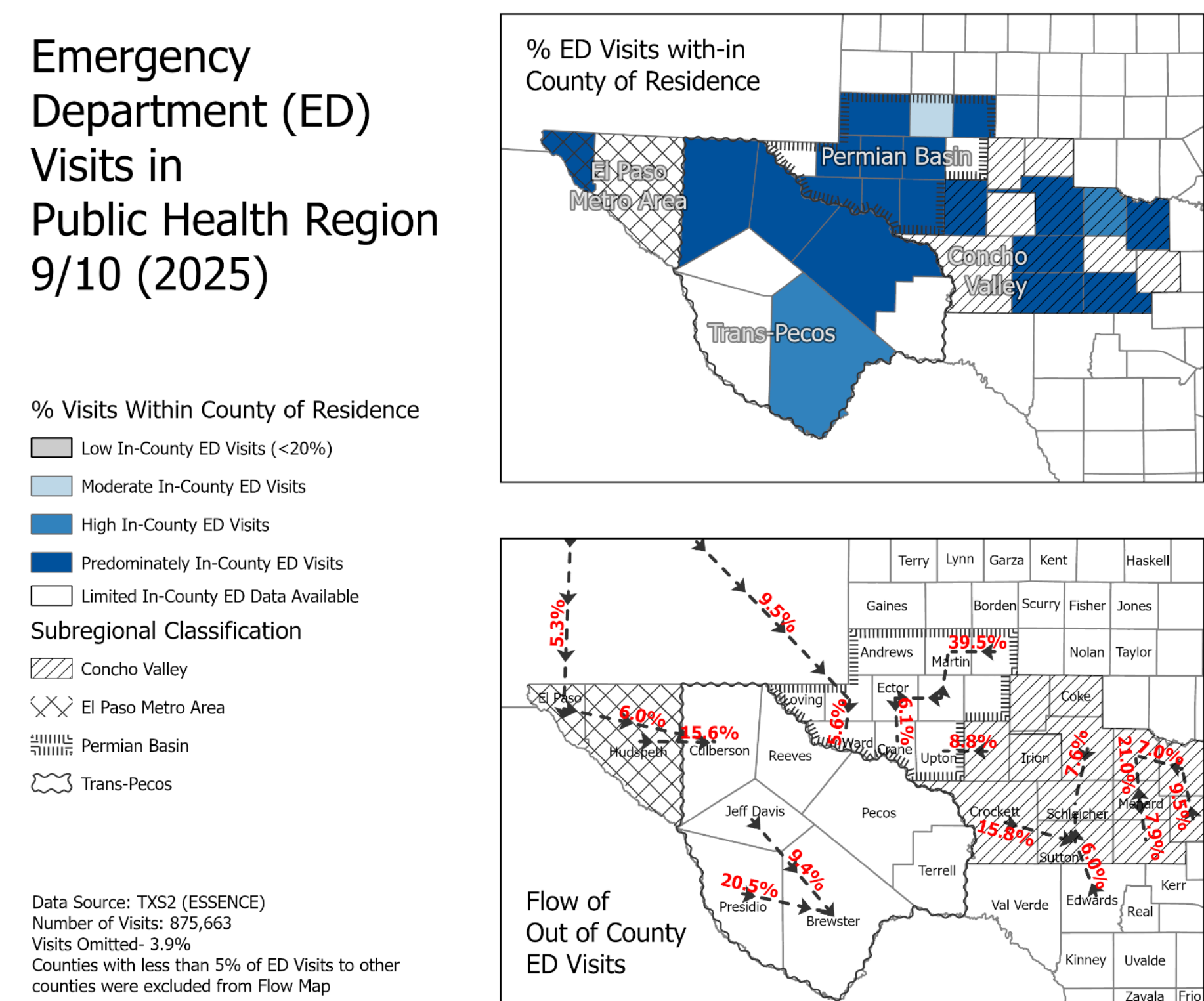


Figure 2. Subregions were informed using emergency department healthcare-seeking patterns across county lines: Permian Basin, El Paso Metro, Concho Valley, and Trans-Pecos.

- Literature Analysis & Needs Assessment:** Pandemic influenza modeling questions were identified through review of literature (Botz et al. & Ghambir et al.). Following selection of a hospital-capacity focus, additional publications were reviewed to inform model structure, parameter selection, and public health applicability.
- Model Selection & Data Inputs:** A deterministic SEIRD+H model was selected as an approachable framework for estimating the impact of community transmission on hospital resources (Figure 1). Compartments represented disease states with daily transition rates between states. Regional healthcare-seeking patterns were evaluated using 2025 ESSENCE emergency department influenza-like illness (ILI) data (Figure 2), which informed division of Public Health Region 9/10 into four primary subregions. Hospital bed and ICU capacity inputs were derived from the Texas Annual Survey of Hospitals (2023). Selected parameters were informed by published literature, while others were estimated for demonstration purposes.
- Model Development in SASViya:** The model was developed in SASViya with six functional modules: (1) Configuration: adjustable baseline parameters (Table 2) and a toggle for ESSENCE surveillance data; (2) Scenario: defines intervention options (masking, vaccination, antivirals, combined) as adjustable multipliers (Table 1); (3) Data: imports surveillance and hospital capacity data, using 8 weeks of regional ILI data to estimate transmission rate and initial infectious burden; (4) Simulation Engine: runs the SEIRD+H model for each day of the defined period and flags when projected demand exceeds hospital capacity; (5) Analytics: calculates epidemic peaks, case totals, and capacity thresholds by subregion; (6) Reporting: generates graphs, summaries, and a PDF output report at end of run.
- Model Execution:** Model was run once with baseline parameters, and two times with ESSENCE data. R_0 was estimated from all three outputs to summarize transmission intensity and confirm whether the model's projections align with what the surveillance would predict.

Results

Table 2: Baseline Parameters

Baseline Value	Initial Exposed per Subregion	β (Transmission Rate)	1/ σ (Incubation rate in days)	1/ γ (Infectious period in days)	% hospitalized from infection	Mean Delay to hospital admission	% hospitalized admit to ICU	Mean Delay from hospital to ICU admission	Mean Hospital LOS	Mean ICU LOS	Hospital Mortality Rate	ICU Mortality Rate
20	20	0.3	2 days	4 days	3%	5 days	25%	2 days	5 days	10 days	2%	20%

The model completed baseline execution in approximately 23 seconds, producing an automated report with graphs and scenario comparisons (Figure 4). Under baseline assumptions, Trans-Pecos subregion showed the highest projected risk of exceeding both hospital bed and ICU capacity over a 340-day period. Combined interventions (masking, vaccination, antivirals, and school closures together) produced the flattest hospital capacity curve in every subregion. The baseline scenario had an R_0 of 1.20, indicating a slow-growing epidemic, consistent with the lower end of published pandemic influenza estimates.

When ESSENCE data was enabled, runtime increased to approximately 14 minutes while the model retrieved and processed eight weeks of syndromic surveillance data (Figure 5 & 6). Because the second run pulled data from late in the 2025–2026 flu season (when activity was winding down), transmission estimates were low and no hospitals were projected to exceed capacity. The calculated R_0 of 0.58 confirms the virus was declining, not spreading. A third run used the eight weeks centered on the December 2025 activity peak ($R_0 = 2.13$), illustrating how the model responds to a more transmission-intensive scenario and better represents conditions under which hospital surge planning becomes critical. This final run exceeded capacity for the Trans-Pecos region in all five scenarios.

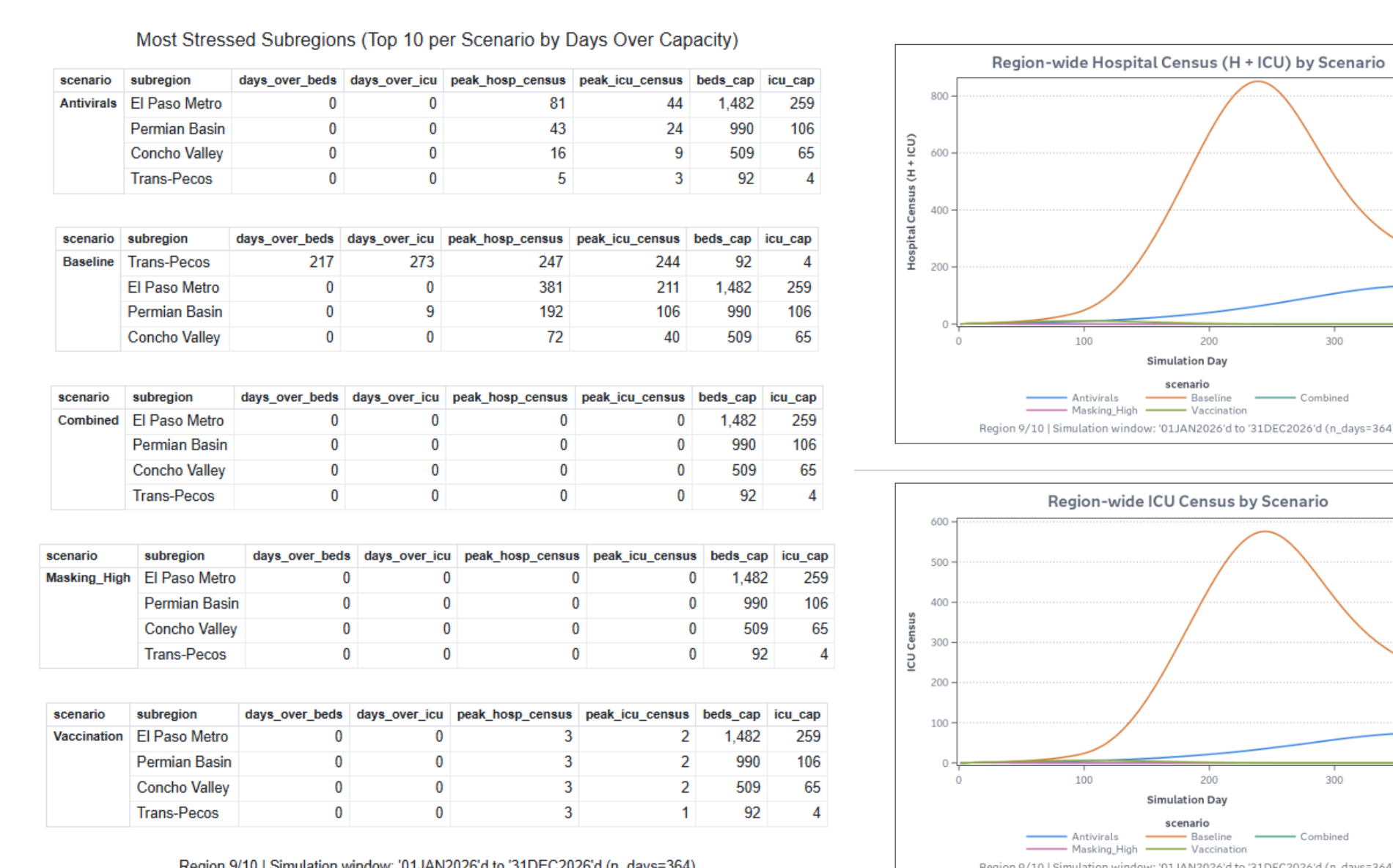


Figure 4. Projected Hospital Demand (Static Parameters) (β : 0.3)

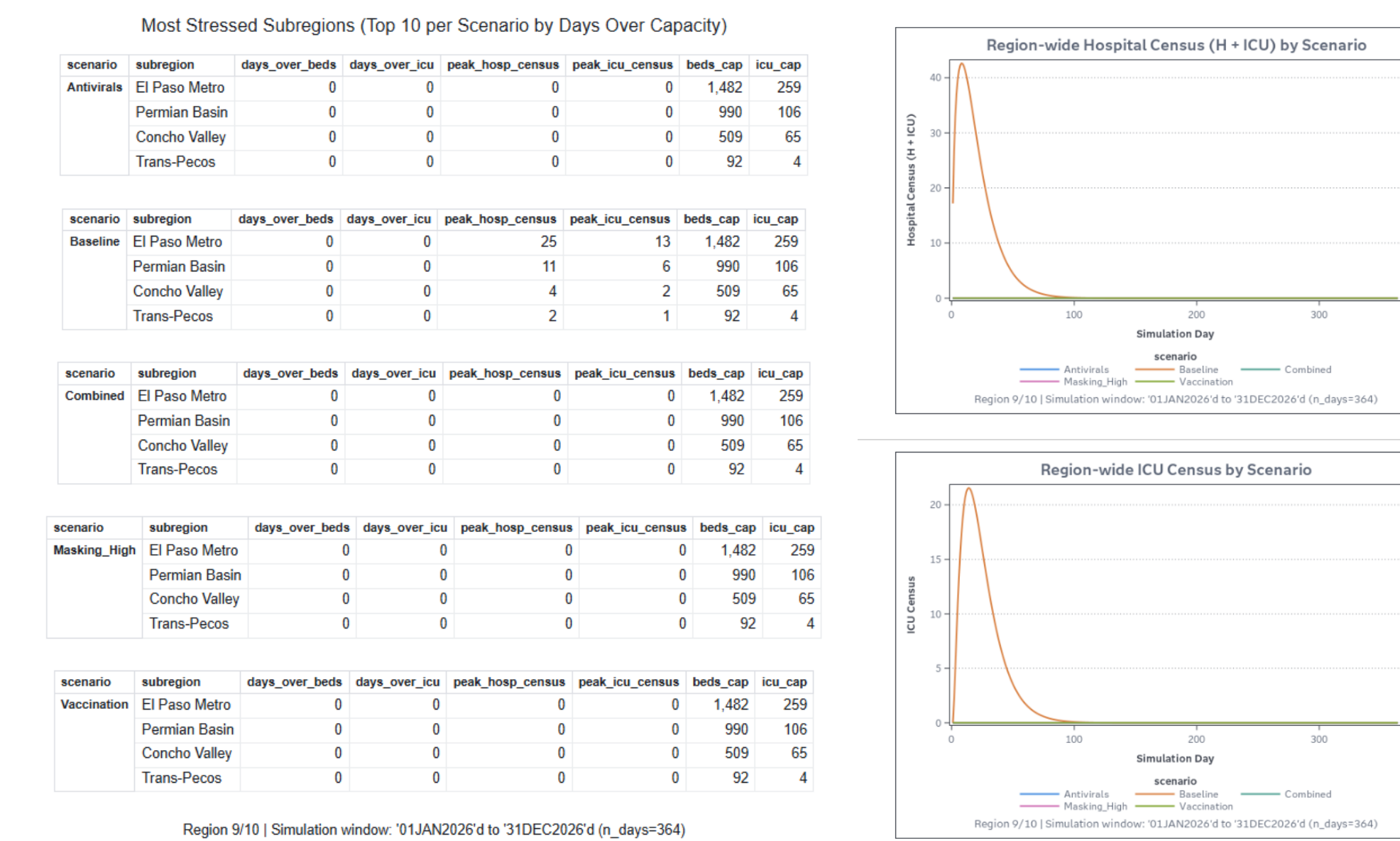


Figure 5. Projected Hospital Demand (ESSENCE-Informed Parameters - 8 Weeks Prior to 11APR26) (β : 0.146)

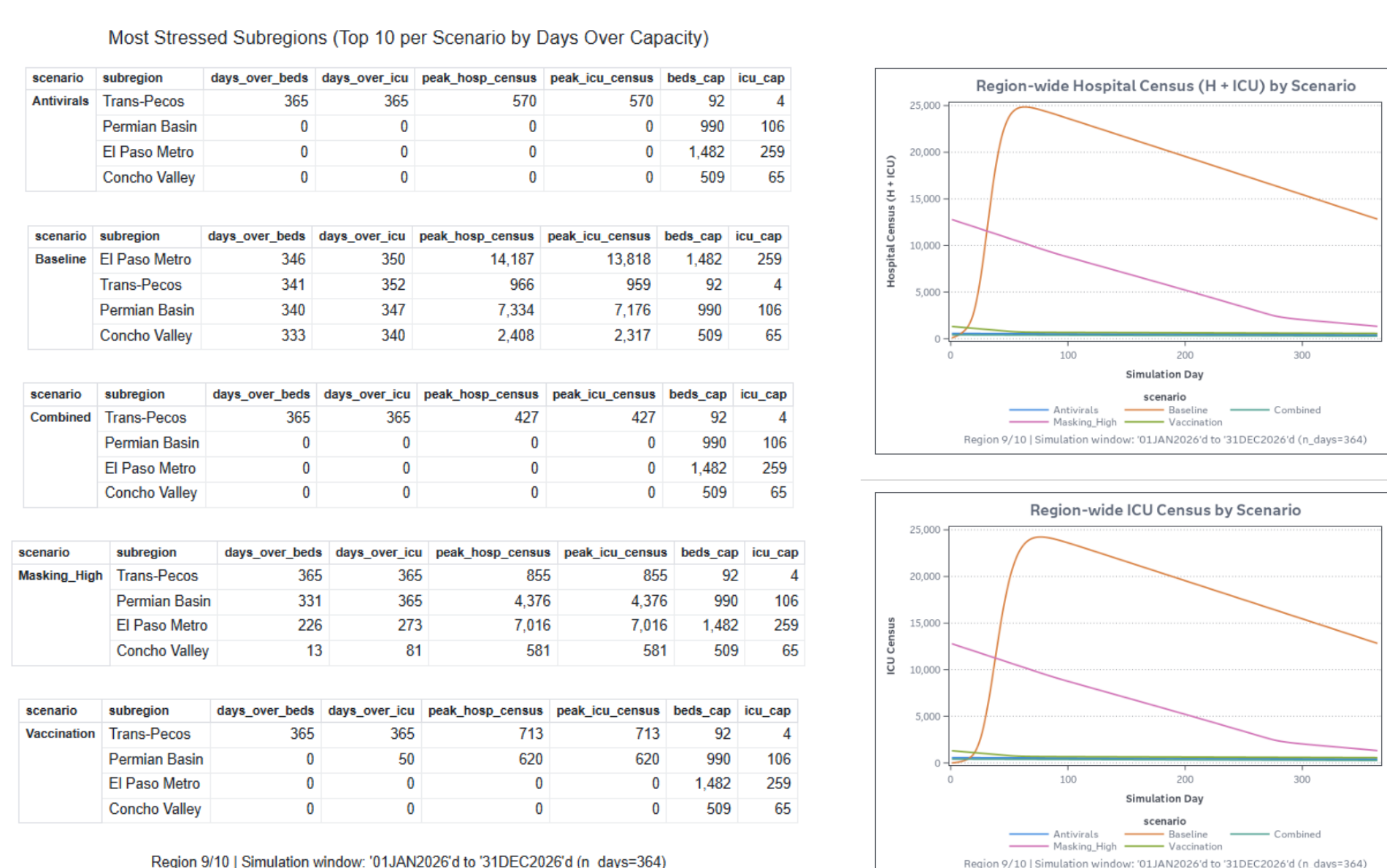


Figure 6. Projected Hospital Demand (ESSENCE-Informed Parameters - 8 Weeks Prior to 27Dec25) (β : 0.533)

Table 1: Scenario Definitions for this Model		
Scenario Name	Definition	Concept within Model
Baseline	No interventions	No change in equation
Vaccination	An effective vaccine is available and the population is vaccinated at a constant rate	0.2% of "S" moves to "R" daily
Antivirals	An effective antiviral is available that shortens infectious period and reduces severity of illness	Reduces Percent Hospitalized (p_{hosp}) by 15%, and increases (γ) thereby reducing the infectious period by 10%
Masking High	High community use of masking and isolation- no vaccination or antiviral available.	β is reduced (Mask multiplier 0.70, Iso multiplier 0.90)
Combined Scenarios	Multiple Interventions used together- Moderate-high adherence across interventions, no single intervention is perfect, effects compound- includes school closures, antivirals, masking, isolation, and vaccination	All interventions listed above together

Primary References

Infectious Disease Modeling Methods as Tools for Informing Response to Novel Influenza Viruses of Unknown Pandemic Potential. 2015. Ghambir et al.

Modeling approaches for early warning and monitoring of pandemic situations as well as decision support. 2022. Botz et al.

Full references available upon request.

Public Health Impact

This framework allows rapid regional scenario planning using existing surveillance systems and may support early preparedness decisions during future respiratory pandemics, including identifying at risk hospitals and targeting surveillance, intervention measures and resource allocation.

Limitations

Results require careful interpretation as outputs are projections, not predictions

Deterministic structure (produces one average outcome, not a range of possibilities)

Population treated as uniform. There are no age or risk group differences (e.g., elderly, immunocompromised)

Simplified mixing within subregions

Parameter uncertainty: some values estimated from literature, appropriate for a first-generation planning tool

Model requires continued validation