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MODELING AND ESTIMATING DYNAMIC CONTRACEPTIVE BEHAVIOR USING SPATIO-TEMPORAL PHYSICS-INFORMED NEURAL NETWORKS

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ABSTRACT

This study develops a Spatio-Temporal Physics-Informed Neural Network (ST-PINN) framework to model contraceptive use dynamics in West Sumatra, Indonesia. Existing models often assume spatial homogeneity and time-invariant parameters, which limit their ability to reflect real-world regional disparities and temporal changes in contraceptive behavior. To address this limitation, this study proposes a hybrid modeling approach that integrates differential equation-based modeling with data-driven learning in a spatio-temporal framework. The proposed model estimates contraceptive adoption, success, and failure rates across 19 districts and cities from 2012 to 2024. This study contributes by (1) developing a spatio-temporal PINN framework for dynamic parameter estimation, (2) integrating spatial and temporal data into a mechanistic model, and (3) providing region-specific insights into contraceptive dynamics. The PINN model achieves high predictive accuracy, with RMSE values ranging from 0.04678 to 0.16132 and R^2 values exceeding 0.85 in several regions with stable data patterns. In contrast, the ST-PINN framework provides enhanced capability in capturing spatial heterogeneity and reveals distinct regional patterns, including consistently high adoption rates in the Mentawai Islands and notable post-2018 changes across multiple regions. However, performance variability across regions indicates the presence of unobserved local factors. These findings highlight the importance of incorporating spatial and temporal heterogeneity in demographic modeling and demonstrate the significance of the ST-PINN framework as a flexible and effective tool for capturing complex regional dynamics and supporting policy-relevant decision-making in reproductive health. Nevertheless, the absence of socio-economic and behavioral variables remains a limitation. Future research should integrate additional data sources to improve model robustness and interpretability.

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1. INTRODUCTION

Population dynamics and reproductive health are intricately connected to the accessibility, adoption, and consistent use of contraceptive methods. In many developing countries, including Indonesia, the family planning program remains a key strategy to control fertility rates, reduce maternal and infant mortality, and improve overall quality of life [1], [2], [3]. Despite years of implementation, disparities in contraceptive use across regions still persist, driven by sociocultural, economic, and infrastructural factors [4], [5]. Key parameters in contraceptive dynamics include the adoption rate (α), which represents the rate at which individuals begin using contraception, the success rate (γ), reflecting effective contraceptive use, and the failure rate (β), indicating unintended outcomes despite contraceptive use. Conventional approaches to modeling contraceptive behavior, such as compartmental models or statistical regressions, often assume constant parameters and spatial homogeneity. However, recent spatial analyses reveal substantial regional variations in contraceptive use that challenge these assumptions. For instance, studies in Ethiopia and Bangladesh have demonstrated significant spatial clustering in modern contraceptive prevalence and non-use, suggesting that parameter values are not uniform across regions [6]-[9]. These findings suggest that adoption rates, success rates, and failure rates vary across both space and time, highlighting the presence of spatio-temporal heterogeneity that cannot be adequately captured by traditional models.

Previous studies on contraceptive modeling have developed along several methodological directions. Statistical and regression-based approaches are widely used to analyze the determinants of contraceptive use and provide descriptive insights based on socio-demographic and behavioral factors; however, these methods are generally limited in capturing complex nonlinear relationships and underlying system mechanisms [6], [10]. In contrast, mechanistic and compartmental modeling approaches, typically formulated using differential equations, enable the representation of dynamic transitions and interactions within the system, offering a more explicit description of temporal evolution. Nevertheless, such models often rely on simplifying assumptions, particularly the use of constant parameters, which may not adequately reflect real-world variability over time [11]. At the same time, spatial analysis approaches have been increasingly applied to capture geographic heterogeneity and regional disparities in contraceptive use through geostatistical and Bayesian frameworks. These models effectively identify spatial clustering and variation across regions but frequently focus on spatial patterns without fully incorporating temporal dynamics [7]. As a result, although each of these approaches contributes valuable insights, they tend to address spatial, temporal, and nonlinear aspects separately rather than within an integrated framework. This limitation highlights the need for hybrid modeling approaches that combine mechanistic and data-driven techniques.

While prior studies have analyzed either spatial variation or temporal trends in contraceptive use, few have developed a unified framework that integrates both. Moreover, the application of advanced machine learning techniques, particularly Physics-Informed Neural Networks (PINNs), to reproductive health modeling remains relatively limited. To the best of our knowledge, existing studies have not yet explored the implementation of a spatio-temporal PINN (ST-PINN) framework for parameter estimation in contraceptive use, particularly within the Indonesian context. This study addresses that gap by introducing a novel hybrid modeling approach that links demographic behavior with underlying physical constraints through neural computation. The integration of these methods not only bridges the gap between data-driven learning and mechanistic modeling but also enables a more realistic understanding of how contraceptive dynamics evolve across both time and space.

Recent advances in scientific machine learning have introduced PINN as a hybrid approach that embeds differential equation systems into neural network training. PINN learns complex dynamics by enforcing physical laws while fitting observational data [12]. Building on this concept, this study extends the approach to a Spatio-Temporal PINN (ST-PINN), enabling simultaneous estimation of time- and location-dependent parameters in a compartmental model of contraceptive use. This methodological innovation expands the traditional scope of demographic modeling, offering a new way to interpret spatio-temporal heterogeneity in reproductive health indicators.

This work makes three main contributions. First, it proposes a spatio-temporal parameter estimation method for the SCNP (Susceptible, Contraceptive, Non-Pregnant, Pregnant) model, allowing α, γ, and β to vary across both time and space. Second, it integrates mechanistic modeling with deep learning to capture nonlinear reproductive behavior dynamics. Third, it generates geo-demographic profiles to identify districts with similar contraceptive use patterns, supporting targeted, evidence-based family planning interventions in West Sumatra. In addition, the study provides an empirical foundation for future extensions of PINN-based frameworks in population dynamics, offering new perspectives on how hybrid models can inform health policy and planning in developing regions.

The integration of PINNs with spatial analysis enables the formulation of geo-demographic profiles, identifying districts with similar patterns of contraceptive dynamics. By estimating parameters such as adoption rate (α), success rate (γ), and failure rate (β) across both time and space, the model uncovers hidden behavioral trends that are not evident from static data analysis. Moreover, the use of K-Means clustering and thematic mapping supports the classification of regions based on dynamic reproductive behavior, providing a strategic tool for policymakers in optimizing family planning efforts [13].

This paper presents a novel framework for modeling and estimating contraceptive use behavior through a combination of mechanistic modeling, neural computation, and spatial analysis. The proposed ST-PINN approach is validated using empirical data from the National Socioeconomic Survey (SUSENAS), covering the period 2012–2024. The findings highlight both the effectiveness and challenges of implementing machine learning models in epidemiological and demographic studies, contributing to the development of adaptive, data-driven population health strategies. The remainder of this paper is organized as follows. Section 2 describes the research methodology, including the SCNP model, PINN framework, and its spatio-temporal extension. Section 3 presents the results and discussion, including parameter estimation and model evaluation. Finally, Section 4 concludes the study and outlines directions for future research.

2. RESEARCH METHODS

This study adopts a quantitative modeling approach that integrates mathematical modeling and machine learning to analyze contraceptive use dynamics. The overall research workflow consists of four main stages: (i) data collection and preprocessing, (ii) formulation of the SCNP differential equation model, (iii) parameter estimation using Physics-Informed Neural Networks (PINN) and its spatio-temporal extension (ST-PINN), and (iv) model evaluation using performance metrics such as Root Mean Square Error (RMSE) and coefficient of determination (R^2). This structured workflow ensures transparency and reproducibility of the proposed framework.

2.1 SCNP Compartmental Structure

This study proposes the SCNP (Susceptible, Contraceptive, Non-Pregnant, Pregnant) model as a novel compartmental framework to represent reproductive behavior dynamics influenced by contraceptive adoption and effectiveness. Unlike conventional compartmental models, the proposed SCNP framework explicitly distinguishes contraceptive states and reproductive outcomes, enabling a more detailed and behaviorally interpretable representation of population dynamics. The framework categorizes the population of women of reproductive age into four main compartments: those susceptible to contraceptive use (S), active contraceptive users (C), non-pregnant women using contraception (N), and pregnant women (P). Transitions between compartments are governed by dynamic parameters such as the adoption rate (α), success rate (γ), and the failure rate of contraceptive methods (β). This structure is designed to capture the dynamics of contraceptive behavior more realistically, particularly within complex spatio-temporal contexts such as in Indonesia.

The model assumes a closed population within each region, and all parameters are treated as time-dependent to capture temporal variations in contraceptive behavior. The system of Ordinary Differential Equations (ODEs) governing transitions is as follows:

$$\frac{dS}{dt} = \pi - \alpha(t)SC + \psi N + \delta P - \mu(t)S, \tag{1}$$

$$\frac{dC}{dt} = \alpha(t)SC - \big(\mu(t) + \gamma(t) + \beta(t)\big)C, \tag{2}$$

$$\frac{dN}{dt} = \gamma(t)C - (\mu(t) + \psi)C, \tag{3}$$

$$\frac{dP}{dt} = \beta(t)C - (\mu(t) + \delta)P. \tag{4}$$

Where:

$\alpha(t)$: Time-dependent contraceptive adoption rate;
$\gamma(t)$: Non-Pregnancy rate (contraceptive success rate);
$\beta(t)$: Pregnancy rate (contraceptive failure rate);
δ : Rate of re-entry into the susceptible category;
$\mu(t)$: Time-dependent exit/mortality rate;
π : The rate of population into Susceptible;
ψ : Return to susceptibility from N.

2.2 Parameter Estimation Using Physics-Informed Neural Networks

A Physics-Informed Neural Network (PINN) is implemented to estimate time-dependent parameters $\alpha(t), \gamma(t), \beta(t)$, and $\mu(t)$. In this study, PINNs are first used to estimate the temporal evolution of parameters by minimizing a composite loss function comprising three components: (i) data loss between predicted and observed values, (ii) residual loss from the SCNP differential equations, and (iii) loss associated with initial conditions. This approach ensures that predictions are both data-driven and consistent with the underlying epidemiological dynamics. PINN incorporates physical laws into neural network training through a composite loss function, ensuring consistency between predictions and the governing system dynamics.

The neural network is implemented as a fully connected feed-forward architecture, where the input consists of time variables and model parameters, and the output corresponds to the predicted contraceptive population $C(t)$. Automatic differentiation is used to compute temporal derivatives required for evaluating the residuals of the differential equations. The total loss function consists of data loss (difference between predicted and observed values), physics loss (ODE residuals), and initial condition loss.

The model is trained using the Adam optimizer with iterative updates until convergence is achieved. Early stopping criteria are applied to prevent overfitting and ensure generalization. The implementation process includes defining the differential equations, preparing observational data, constructing the neural network, computing automatic differentiation, training the model, and validating the results.

The architecture of a PINN consists of a neural network $f_\theta(x,t)$ parameterized by weights θ, trained not only to fit data but also to minimize the governing partial differential equation. For a system governed by a general PDE:

$$N[u(x,t)] = 0, (x,t) \epsilon\ \Omega\ x\ [0,T] \tag{5}$$

where $N[u(x,t)]$ is a non-linear differential operator; the PINN is trained by minimizing a composite loss function.

$$L(\theta) = L_{data} + L_{physics} + L_{\frac{BC}{IC}}, \tag{6}$$

$$L_{physics} = \frac{1}{N_f}\sum_{i=1}^{N_f} |N[f_\theta(x_i,t_i)]|^2 \ , \tag{7}$$

where:

L_{data} : The mean squared error between observed data and predicted output;
$L_{physics}$: Residual loss of the PDE;
$L_{BC/IC}$: Loss from initial and boundary conditions.

This formulation ensures that the neural network learns functions that satisfy the physical laws even in regions where no data are available. PINNs have been applied to forward and inverse problems, including parameter estimation, system identification, and control [14].

In inverse problems, PINNs are used to estimate unknown parameters λ in the governing equation:

$$(N[u(x,t);\lambda]) = 0 \tag{8}$$

The parameter λ is then treated as a learnable variable, optimized jointly with the neural network weights θ during training. The training process simultaneously optimizes θ and λ to minimize the total loss function.

This makes PINN highly effective in the context of system identification, dynamic parameter estimation, and data-driven model calibration.

The following flowchart illustrates the steps of parameter estimation using PINN:

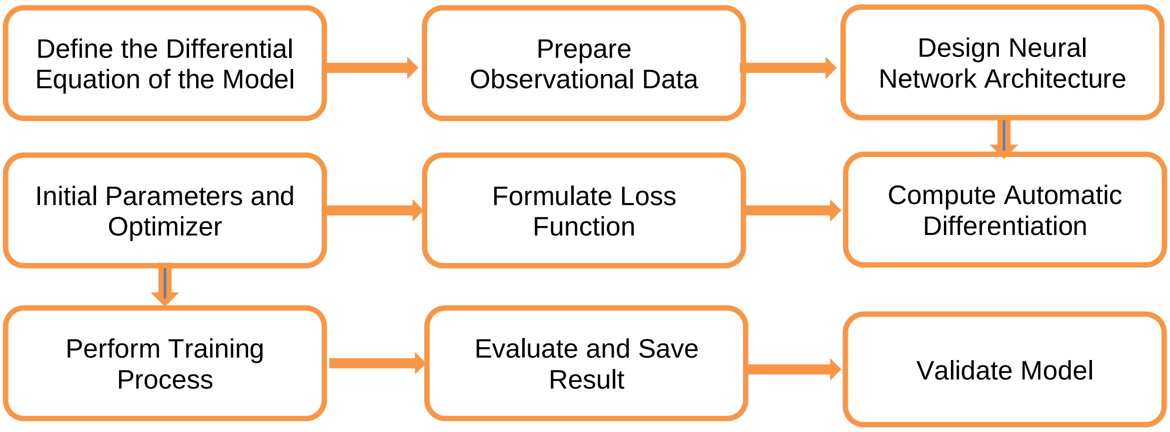


Figure 1. Steps of Parameter Estimation using PINN

2.3 Spatio-Temporal Physics-Informed Neural Networks (ST-PINN)

Spatial heterogeneity plays a crucial role in modeling contraceptive behavior, as regional differences in socio-cultural conditions, healthcare access, and policy implementation lead to varying adoption and usage patterns. To capture this variability, the methodology is extended using a Spatio-Temporal PINN (ST-PINN), enabling simultaneous estimation of time- and location-dependent parameters in a compartmental model of contraceptive use. In this framework, model parameters are treated as functions of both time (t) and location (x), $\alpha(t,x), \gamma(t,x)$, and $\beta(t,x)$. This is particularly relevant for problems involving spatial heterogeneity, such as population dynamics, infectious disease spread, and environmental diffusion [15]. The model learns a solution $u(x,t)$ to a PDE of the form:

$$\frac{\partial u(x,t)}{\partial t} + N_x[u(x,t)] = 0, \quad (x,t) \epsilon\, \Omega\ x\ [0,T], \tag{9}$$

where $N_x[u(x,t)]$ involves spatial derivatives such as $\frac{\partial u}{\partial t}, \frac{\partial^2 u}{\partial x^2}$. The ST-PINN includes both spatial and temporal collocation points during training, and its loss function remains similar in form:

$$L_{ST-PINN} = L_{data} + L_{PDE} + L_{\frac{BC}{IC}}\,. \tag{10}$$

In spatially varying systems, the governing PDE may also include space-dependent parameters $\lambda(x,t)$, making inverse modeling more challenging. In such cases, the PINN is trained not only to approximate $u(x,t)$, but also to infer $\lambda(x,t)$ using automatic differentiation to compute the spatio-temporal residuals of the system. Automatic differentiation enables accurate and efficient computation of derivatives directly from the neural network without requiring numerical discretization, thereby improving stability and precision in capturing complex system dynamics.

Parameter estimation uses district-level data on contraceptive use in West Sumatra from 2012 to 2024. This dataset, sourced from annual observational data on contraceptive use in West Sumatra Province [16]-[20], enables the neural network to learn historical trends and spatial patterns.

2.4. Data Source and Preprocessing

The dataset used in this study consists of annual contraceptive use data obtained from the National Socioeconomic Survey (SUSENAS) for 19 districts and cities in West Sumatra from 2012 to 2024. Prior to training, the data are normalized and smoothed to reduce noise and improve model stability. Missing values are handled using interpolation techniques.

2.5 Model Evaluation

To evaluate model performance, the dataset is divided into training and testing subsets. The trained model is validated using unseen data to assess its generalization capability. Model performance is evaluated using Root Mean Square Error (RMSE) and coefficient of determination (R^2).

3. RESULTS AND DISCUSSION

This section presents the outcomes of parameter estimation conducted using Physics-Informed Neural Networks (PINN) and its spatio-temporal extension (ST-PINN) applied to contraceptive use data in West Sumatra. The analysis considers temporal data (2012–2024), spatial variation across districts, and dynamic parameter estimation under SCNP model constraints. The comparison is conducted between PINN and ST-PINN frameworks to evaluate the contribution of spatial modeling. The results include both time-dependent and spatially varying estimates of key behavioral parameters: contraceptive adoption rate (α), success rate (γ), and failure rate (β). The performance of each modeling approach is evaluated using accuracy metrics such as RMSE and R^2, and the findings are discussed in relation to regional demographic patterns and policy relevance. Comparative insights between the PINN and ST-PINN frameworks are also provided to highlight the advantages of incorporating spatial heterogeneity in reproductive behavior modeling.

3.1 Parameters of SCNP Model Using PINN

To ensure the reliability of the model, the dataset is divided into training and testing subsets. The training phase is used to optimize the neural network parameters, while the testing phase evaluates the model's ability to predict unseen data. This procedure ensures that the model does not overfit the training data and provides a reliable measure of generalization performance. The parameter estimation process using PINN begins with the definition of the SCNP differential equation system and preparation of observational data $C(t)$ for the period 2012–2024. The neural network is constructed with inputs consisting of time and model parameters, and outputs corresponding to predicted $C(t)$. Automatic differentiation is applied to compute temporal derivatives required for evaluating the residuals of the differential equations. The total loss function combines data loss and physics loss to ensure consistency between predictions and system dynamics.

$$L_D(\hat{C}) = \omega_D \cdot \frac{1}{N_D} \sum_{j=1}^{N_D} \left(\hat{C}(t_j) - C_{obs}(t_j)\right)^2 . \tag{11}$$

Where:

N_D : Number of data points;
$\hat{C}(t)$: NN prediction result;
$C_{obs}(t)$: actual contraceptive use data;
ω_D : data weight.

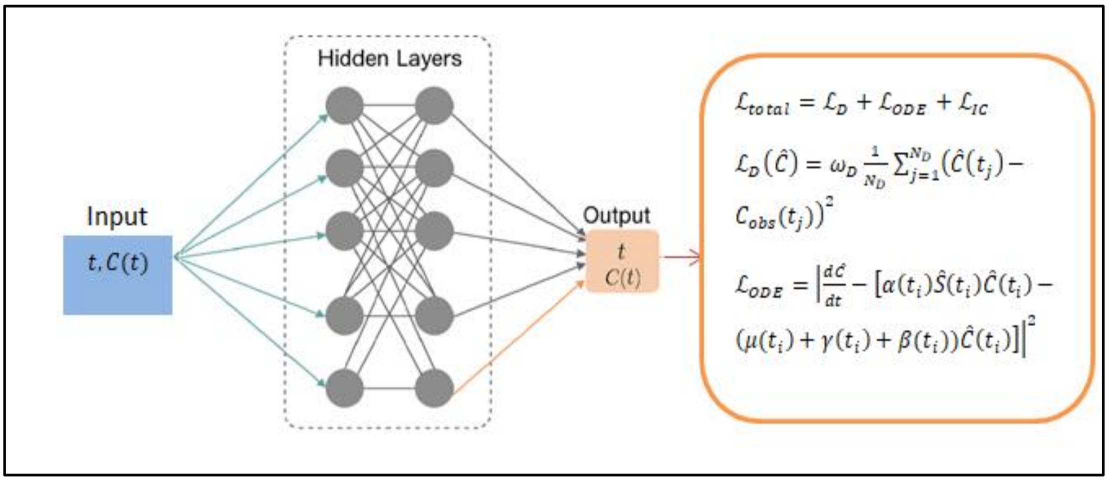


Figure 2. Physics-Informed Loss (Residual ODE SCNP)

$$L_{ODE} = \frac{1}{N_C}\sum_{i=1}^{N_C}\left[\left|\frac{d\hat{C}}{dt} - \left[\alpha(t_i)\hat{S}(t_i)\hat{C}(t_i) - (\mu(t_i) + \gamma(t_i) + \beta(t_i))\hat{C}(t_i)\right]\right|^2\right], \tag{12}$$

$$L_{total} = L_D + L_{ODE} + L_{IC}. \tag{13}$$

Where N_C is the number of physics collocation points, $\alpha(t), \beta(t), \gamma(t)$ are the parameters estimated through NN, and $\hat{C}, \hat{N}, \hat{P}$ are predictions from neural networks.

Initial Condition Loss L_{IC} is given by the following Eq. 14:

$$L_{IC} = \omega_0 \cdot \left(\hat{C}(t_0) - C_0\right)^2, \tag{14}$$

where C_0 : The initial value of contraceptive use and ω_0 : weight for initial penalty.

After training, the PINN model is applied to estimate SCNP parameters and evaluate predictive performance across districts using observed data. In the training performance and convergence stage, the PINN produces parameter estimates that are consistent with both the observational data and the structure of the SCNP differential model. The parameters obtained include the contraceptive adoption rate (α), the success rate of contraceptive use (γ), and the failure rate or transition to pregnancy (β), all derived from the optimization of the loss function.

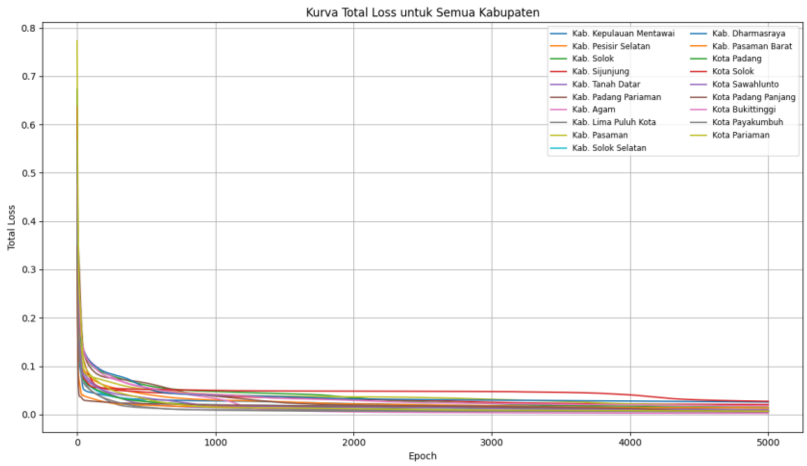


Figure 3. Loss Curves for All Districts/Cities in West Sumatra

As shown in Fig. 3, the loss curves for all districts and cities in West Sumatra, show how the total training loss evolves over 5000 epochs for each region's PINN model. Overall, the loss curves demonstrate a consistent pattern across regions: a sharp decrease during the early epochs followed by convergence to low, stable values, indicating practical model training and optimization. This convergence indicates that the optimization process successfully minimizes the residuals of the SCNP differential equations, ensuring consistency between the learned parameters and the governing system. Some regions, such as Kota Padang, Kota Payakumbuh, and Kabupaten Dharmasraya, exhibit rapid convergence with low final loss values, indicating a strong fit between the model and the observed data. In contrast, areas like Kabupaten Pasaman Barat and Kota Pariaman demonstrate slightly higher residual losses, which may reflect the presence of noisier data or underlying complexities in contraceptive use dynamics. Nevertheless, the general downward trend across all curves confirms that the training process was successful in minimizing the objective function and learning region-specific contraceptive dynamics. The variation in convergence speed across regions may be attributed to differences in data quality, sample size, and the stability of contraceptive behavior over time. Regions with smoother and more consistent data patterns tend to exhibit faster convergence, as the model can more easily learn underlying trends. In contrast, slower convergence or higher residual loss may indicate noisier observations, abrupt behavioral changes, or unobserved socio-demographic factors, which can challenge the learning process and affect model generalization. These findings suggest that convergence behavior can serve as an indirect indicator of data reliability and model sensitivity to regional variability. Regions with lower final loss values tend to correspond to areas with lower RMSE and higher R^2 values, indicating more stable and predictable contraceptive dynamics. Conversely, regions with higher residual loss may reflect data noise or unobserved behavioral variability. The estimated parameter values for each district/city are summarized in Table 1.

Table 1. Summary of the SCNP Parameter Values for All Districts/Cities in West Sumatra

Districts/Cities	Parameters			Districts/Cities	Parameters		
	Alpha	Gamma	Beta		Alpha	Gamma	Beta
Kab. Kep. Mentawai	1.7980	0.8752	0.2403	Kab. Dharmasraya	2.8627	0.7907	0.0007
Kab. Pesisir Selatan	1.6542	0.7756	0.3848	Kab. Pasaman Barat	1.9891	0.8117	0.3669
Kab. Solok	1.5858	0.8016	0.0046	Kota Padang	1.8567	0.9145	0.5610
Kab. Sijunjung	1.2650	0.8051	0.3418	Kota Solok	3.8552	0.7002	0.0003
Kab. Tanah Datar	1.5028	0.7050	0.4757	Kota Sawahlunto	2.8683	0.7031	0.0040
Kab. Padang Pariaman	1.4793	0.7885	0.2878	Kota Padang Panjang	1.4377	0.9134	0.6908
Kab. Agam	1.2600	0.8031	0.2969	Kota Bukittinggi	0.7677	0.7873	0.2097
Kab. Lima Puluh Kota	0.2681	0.8287	0.4123	Kota Payakumbuh	1.6419	0.7011	0.0019
Kab. Pasaman	1.8669	0.7007	0.0020	Kota Pariaman	3.0879	0.7002	0.0004
Kab. Solok Selatan	2.3062	0.7004	0.0008				

The results in Table 1 reveal substantial spatial variation in contraceptive use dynamics. For example, Kota Solok and Kota Pariaman exhibit high adoption rates, while Kabupaten Lima Puluh Kota shows relatively low adoption levels. High values of γ across most regions indicate effective contraceptive use, while near-zero β values in several districts suggest low failure rates. These findings highlight the ability of the PINN model to capture both stable and heterogeneous behavioral patterns across regions. The PINN parameter estimates reveal notable spatial variation in contraceptive use across West Sumatra. Kota Solok and Kota Pariaman show exceptionally high adoption rates ($\alpha > 3.0$), while Kabupaten Lima Puluh Kota records the lowest value (0.2681). Contraceptive success rates (γ) are generally high throughout the region (> 0.75), with Kota Padang and Kota Padang Panjang exceeding 0.91. Failure rates or transitions to pregnancy (β) are very low in many areas, approaching zero in places such as Kota Solok and Kota Pariaman. Model performance is strong, with low RMSE values in most regions, the lowest being in Agam, Pasaman Barat, and Kabupaten Tanah Datar (< 0.006), and high R^2 values, indicating close alignment between the model's predictions and actual data. These differences highlight the effectiveness of the PINN framework in capturing the dynamics of contraceptive use while also revealing interregional disparities that are critical for policy development. These variations may be influenced by differences in access to healthcare services, socio-cultural acceptance of contraception, education levels, and the effectiveness of local family planning programs. Regions with higher adoption rates (α) may reflect stronger outreach programs and better public awareness, while lower values may indicate limited access or cultural resistance. Similarly, high success rates (γ) suggest effective and consistent contraceptive use, whereas near-zero failure rates (β) may indicate either highly effective contraceptive methods or potential underreporting in the data. In practice, these differences highlight the need for region-specific policy interventions, where areas with lower adoption or higher variability may require targeted education, improved healthcare access, and more tailored family planning strategies.

To gain a deeper understanding of the spatial variation in contraceptive use dynamics across West Sumatra, the regions were grouped based on the estimated values of the contraceptive adoption rate (α), success rate γ), and failure rate or transition to pregnancy (β) obtained from the PINN model. Using the tertile method, each parameter was divided into three categories: low, medium, and high. This approach facilitates the identification of regions with similar characteristics in terms of adoption level and contraceptive effectiveness. Such categorization is expected to provide a clearer picture of interregional differences and support the development of more targeted intervention strategies tailored to the parameter profiles of each area. The tertile method was chosen due to its simplicity and robustness in categorizing continuous variables into balanced groups without requiring distributional assumptions. This approach ensures that each category contains a comparable number of regions, facilitating meaningful comparisons across groups. As a result, the interpretation of spatial patterns becomes more intuitive, allowing policymakers to identify priority regions based on relative parameter levels rather than absolute thresholds.

The following is a thematic map of West Sumatra based on adoption rate, success rate, and failure rate:

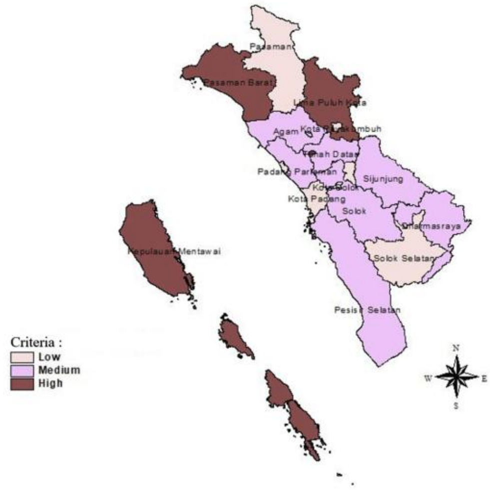


Figure 4. Clustering West Sumatra based on Gamma Value

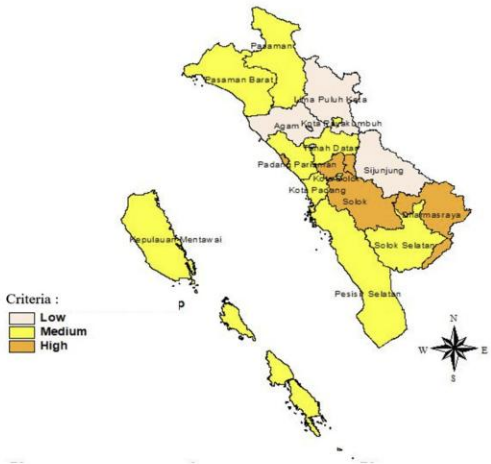


Figure 5. Clustering West Sumatra based on Alpha Value

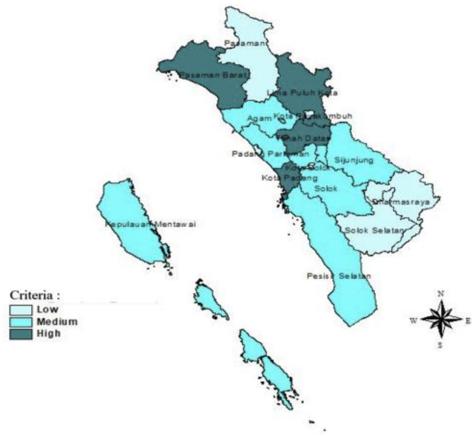


Figure 6. Clustering West Sumatra based on Beta Value

Fig. 4 through Fig. 6 show how the districts and cities of West Sumatra are classified, based on the estimated values of the γ , α, and β parameters. These maps reveal differences in how contraceptives are used across the province of West Sumatra. The observed differences are consistent with the variations in model performance shown in Table 1. Generally, areas with more balanced parameter values, such as a higher gamma (indicating more effective contraceptive use) and a moderate beta (suggesting fewer failures), demonstrate better model performance. This is supported by lower RMSE values and higher R^2 scores. For instance, Agam, Lima Puluh Kota, and Tanah Datar not only exhibit highly accurate predictions but also correspond to parameter groups that are more favourable. Conversely, regions characterised by less stable or less advantageous parameter configurations frequently yield models with diminished predictive efficacy. For example, Solok City shows the highest RMSE and the lowest R^2 value. This indicates that the model doesn't fully capture the characteristics of this area. This discrepancy may stem from greater variability in parameter values or the influence of local socio-demographic variables, such as income levels, educational attainment, and population density, which, although not explicitly incorporated into the model, can significantly affect the accuracy of outcome predictions. The results essentially demonstrate a strong link between how well the model performs and how key parameters are spread out in space. This highlights the importance of adjusting parameters based on specific regions. Doing so will help the model better represent local behaviours, which will then improve the accuracy of its overall predictions.

Thematic maps of contraceptive adoption rate (α), success rate (γ), and failure rate (β) across districts and cities in West Sumatra in Fig. 4 – Fig. 6 are estimated using the Physics-Informed Neural Network (PINN) framework. The maps illustrate clear spatial disparities: α is highest in Solok City and Pariaman City (> 3.0) and lowest in Lima Puluh Kota Regency (0.27); γ remains high in most regions (> 0.75), with peaks above 0.91 in Padang and Padang Panjang; β is notably low in several areas, approaching zero in Solok City and Pariaman City. Such spatial heterogeneity aligns with findings from regional contraceptive studies [21] that emphasize the role of socio-economic and accessibility factors in shaping contraceptive dynamics. These maps complement the statistical results, providing a visual tool for identifying priority areas for targeted family planning interventions.

Table 2. The RMSE and R^2 Values for All Districts/City in West Sumatra

Districts/City	RMSE	R^2	Districts/City	RMSE	R^2
Kab. Kepulauan Mentawai	0.0074	0.8558	Kab. Dharmasraya	0.0208	0.7705
Kab. Pesisir Selatan	0.0061	0.8933	Kab. Pasaman Barat	0.0024	0.9488
Kab. Solok	0.0149	0.8188	Kota Padang	0.0064	0.9218
Kab. Sijunjung	0.0165	0.7768	Kota Solok	0.0350	0.4195
Kab. Tanah Datar	0.0058	0.9302	Kota Sawahlunto	0.0054	0.8808
Kab. Padang Pariaman	0.0109	0.8526	Kota Padang Panjang	0.0068	0.8476
Kab. Agam	0.0026	0.9785	Kota Bukittinggi	0.0173	0.7730
Kab. Lima Puluh Kota	0.0047	0.9339	Kota Payakumbuh	0.0060	0.9062
Kab. Pasaman	0.0149	0.6693	Kota Pariaman	0.0055	0.9355
Kab. Solok Selatan	0.0094	0.8120			

The results in Table 2 show that the proposed model is very effective at predicting events in most of West Sumatra's cities and districts. Low RMSE values and high R^2 scores show the model's accuracy. The best models are Agam, Lima Puluh Kota, and Tanah Datar because their R^2 values are all over 0.93. Such performance means that the model can show how the data changes over time in a way that is correct. However, some places, like Kota Solok, do not do as well. The highest R^2 value is 0.4195, and the lowest RMSE value is 0.0350. This evidence makes it possible that the model doesn't fully show how things work in these areas. Such discrepancies could be due to the data being less consistent or the model lacking socio-demographic characteristics. These numbers indicate that the model works differently in different places.

In addition to the previously highlighted districts, a more detailed review of the RMSE and R^2 values across all 19 districts and cities in West Sumatra reveals consistent performance of the PINN model. Most regions exhibit RMSE values below 0.01, indicating a minimal average deviation between predicted and observed contraceptive use. Districts such as Kabupaten Lima Puluh Kota, Kabupaten Padang Pariaman, and Kota Padang Panjang also show reliable model performance with R^2 values above 0.84, suggesting that the model captures more than 84% of the variation in actual data. Similarly, Kota Payakumbuh and Kabupaten Pesisir Selatan show high predictive fidelity, both in terms of low RMSE and R^2 values above 0.89.

On the other hand, Kota Solok stands out with the highest RMSE value and a low R^2, indicating that the model struggled to capture the contraceptive dynamics in this area, possibly due to local behavioral anomalies or data inconsistencies. Kabupaten Dharmasraya also shows relatively high RMSE and moderate R^2 (0.7705), which may reflect more complex, nonlinear transitions in contraceptive use patterns. Overall, the combination of low RMSE and high R^2 across most districts demonstrates the robustness of the PINN model in learning and generalizing contraceptive use trends. Furthermore, variations in model accuracy across regions underscore the importance of considering local demographic and behavioral heterogeneity when applying predictive frameworks for public health.

3.2 Estimation Parameter of SCNP Model Using Spatio-Temporal PINN

The ST-PINN model extends the PINN framework by incorporating spatial heterogeneity in parameter estimation. Similar to the PINN model, the ST-PINN framework is evaluated using a training-testing data split to ensure that spatial and temporal generalization is properly assessed. We define $\alpha(t,x), \gamma(t,x)$, and $\beta(t,x)$ as spatio-temporal parameters, where t is time and x is spatial location (for example, coordinates, district/city area codes). We extend the deterministic ODE system to spatio-temporal functions.

$$\frac{\partial S(t,x)}{\partial t} = -\alpha(t,x)C(t,x)S(t,x) + N\psi(t,x) + \delta P(t,x) - \mu S(t,x) + \pi(x), \tag{15}$$

$$\frac{\partial C(t,x)}{\partial t} = \alpha(t,x)C(t,x)S(t,x) - \big(\mu + \gamma(t,x) + \beta(t,x)\big)C(t,x), \tag{16}$$

$$\frac{\partial N(t,x)}{\partial t} = \gamma(t,x)C(t,x) - (\mu + \psi)(t,x)C(t,x), \tag{17}$$

$$\frac{\partial P(t,x)}{\partial t} = \beta(t,x)C(t,x) - (\mu + \delta)P(t,x). \tag{18}$$

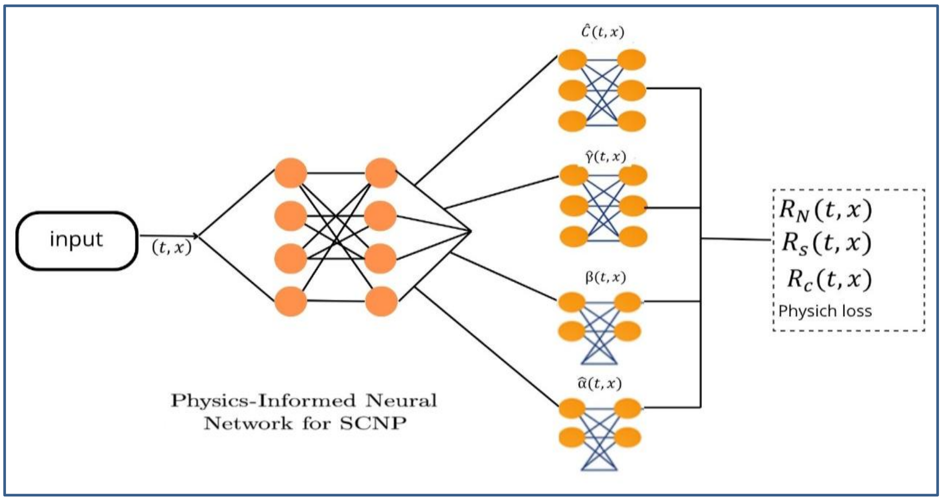


Figure 7. Visual Architecture Chart of Spatio-Temporal PINN for SCNP Model

All functions of S and C depend on time and location $f(t,x)$. $\alpha(t,x), \gamma(t,x)$, and $\beta(t,x)$ are the spatio-temporal dynamic parameters that need to be estimated, $\pi(x)$ is the population entry rate into S, which is fixed per region. $\pi(x)$ is the population entry rate to S, which is fixed per region. From Fig. 7, the Neural Network formulation is explained. Input PINN:

$$\text{Input: } (t,x)\epsilon\big[t_0, t_f\big] * \Omega$$

$$\text{With output: } \hat{C}(t,x), \hat{\alpha}(t,x), \hat{\beta}(t,x), \hat{\gamma}(t,x).$$

PINN is trained by minimizing the total loss, which is given by:

$$L_{total} = L_{data} + \lambda_{phys}L_{phys} + L_{init}L_{init}. \tag{19}$$

The Data Loss:

$$L_{data} = \frac{1}{N_d}\sum_{1=1}^{N_d}\left(\hat{C}(t_i,x_i) - C_{data}(t_i,x_i)\right)^2. \tag{20}$$

Physics Loss (ODE residuals):

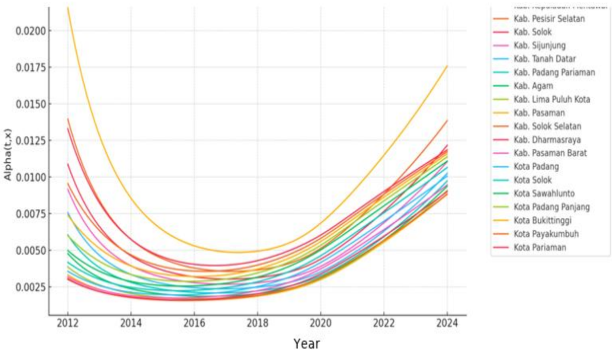
$$R_C(t,x) = \frac{\partial \hat{C}}{\partial t}(t,x) - \left[\hat{\alpha}(t,x)\hat{C}(t,x)\hat{S}(t,x) - \left(\mu + \hat{\gamma}(t,x) + \hat{\beta}(t,x)\right)\hat{C}(t,x)\right], \tag{21}$$

$$L_{physics} = \frac{1}{N_C}\sum_{j=1}^{N_C} R_C^2(t_j, x_j), \tag{22}$$

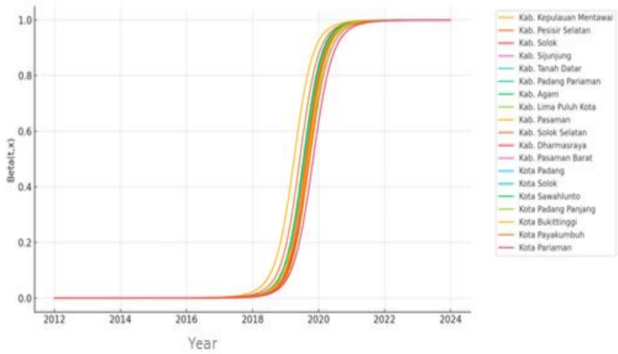
$$L_{init} = \left(\hat{C}(t_0, x) - C_0(x)\right)^2. \tag{23}$$

3.3 Training Performance and Convergence

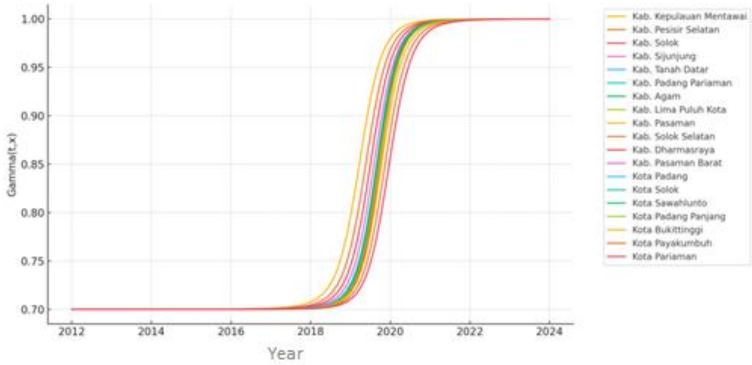
The following is a visualization of the parameter estimates $\alpha(t,x)$ (the rate of contraceptive adoption), $\gamma(t,x)$ and $\beta(t,x)$ for each district from 2012 to 2024 based on the spatio-temporal PINN model. The lines show the variation of alpha values over time for each region.



(a)



(b)



(c)

Figure 8. Estimated Parameters by District and Year
(a) $\boldsymbol{\alpha(t,x)}$, (b) $\boldsymbol{\beta(t,x)}$, (c) $\boldsymbol{\gamma(t,x)}$

As illustrated in Fig. 8, the estimated parameters exhibit clear temporal-spatial patterns across districts. The adoption rate (α) shows a U-shaped pattern across most regions, decreasing until around 2016–2018 and increasing thereafter. The temporal-spatial dynamics of contraceptive behavior in West Sumatra, as depicted in the estimated parameters $\alpha(t,x)$, $\beta(t,x)$ and $\gamma(t,x)$, reveal meaningful patterns across districts from 2012 to 2024. As shown in Fig. 8 (a), the adoption rate (α) demonstrates a consistent U-shaped trajectory in most regions, declining from 2012 and reaching a trough around 2016 to 2018 before increasing again toward 2024. This pattern may reflect delayed but eventually intensified contraceptive campaigns or shifting sociocultural acceptance. Notably, Kabupaten Kepulauan Mentawai exhibits consistently higher adoption rates, possibly indicating stronger interventions or greater program outreach.

In contrast, both the failure rate (β) and the success rate (γ) in Fig. 8 (b) and Fig. 8 (c) exhibit sharp sigmoid-like increases, particularly after 2018. These parameters remained stable in earlier years but rose rapidly during 2018–2020 and stabilized near one by 2022–2024. This pattern may reflect delayed policy impact or changes in public acceptance of contraceptive methods. Regions such as Kabupaten Kepulauan Mentawai consistently show higher adoption rates, indicating stronger program effectiveness. Table 3 presents a summary of the SCNP parameter values estimated for each district/city in West Sumatra.

Table 3. Summary of the SCNP Parameter Values for All Districts/Cities in West Sumatra

Districts/Cities	Parameters			Districts/Cities	Parameters		
	Alpha	Gamma	Beta		Alpha	Gamma	Beta
Kab. Kep. Mentawai	0.1191	0.8320	0.3934	Kab. Dharmasraya	0.4772	0.8168	0.3692
Kab. Pesisir Selatan	0.2537	0.8261	0.3785	Kab. Pasaman Barat	0.2967	0.8212	0.3863
Kab. Solok	0.4107	0.8240	0.3747	Kota Padang	0.1885	0.8255	0.4018
Kab. Sijunjung	0.3987	0.8260	0.3818	Kota Solok	0.5413	0.8291	0.4126
Kab. Tanah Datar	0.3505	0.8294	0.3906	Kota Sawahlunto	0.7590	0.8330	0.4236
Kab. Padang Pariaman	0.6942	0.8269	0.3798	Kota Padang Panjang	0.6132	0.8231	0.4032
Kab. Agam	0.5419	0.8251	0.3736	Kota Bukittinggi	0.4796	0.8150	0.3867
Kab. Lima Puluh Kota	0.6081	0.8206	0.3647	Kota Payakumbuh	0.1420	0.8229	0.4013
Kab. Pasaman	0.8964	0.8105	0.3431	Kota Pariaman	0.1396	0.8181	0.3884
Kab. Solok Selatan	0.6805	0.8129	0.3534				

The parameter estimation results from the Spatio-Temporal Physics-Informed Neural Network (ST-PINN) model reveal significant variation across districts and cities in West Sumatra in terms of contraceptive use dynamics. The analyzed parameters include the contraceptive adoption rate (α), the success rate of contraceptive use (γ), and the failure rate of contraceptive use (β). There is significant variation between regions in contraceptive adoption rates (α), with some regions, such as Kabupaten Pasaman and Kota Sawahlunto, showing high adoption. In contrast, regions such as Kabupaten Kepulauan Mentawai and Kota Pariaman remain low, signaling the need for locally based policy interventions. Contraceptive success scores (γ) are generally high across regions (>0.81), indicating the effectiveness of the methods used, although some regions continue to require improvements in the quality of education and services. Contraceptive failure (β) remains a challenge in some urban areas such as Kota Padang and Kota Solok, indicating the need for evaluation of contraceptive methods and improved adherence.

To evaluate the performance of the Spatio-Temporal Physics-Informed Neural Network in estimating contraceptive dynamics, two key metrics are employed: RMSE and R^2. Recent studies in spatial-temporal epidemiological modeling support the use of these metrics. For example, the EpiGNN framework reduced RMSE by 9.48 % compared to the best baseline model in regional epidemic forecasting [22]. Similarly, a PINN-based inverse modeling approach for epidemic systems demonstrated up to an order-of-magnitude improvement in parameter estimation accuracy and 20× better computational efficiency compared to hybrid methods [15]. Another spatio-temporal GNN study reported R^2 values up to 0.899 for infection trend prediction, underscoring the robustness of such models in capturing complex spatial-temporal patterns [23]. The following table summarizes the RMSE and R^2 values across 19 districts and cities in West Sumatra:

Table 4. Summary of the RMSE and R^2 Values across 19 Districts and Cities in West Sumatra

Districts/Cities	RMSE	R^2	Districts/Cities	RMSE	R^2
Kab. Kepulauan Mentawai	0.1873	0.4475	Kab. Dharmasraya	0.2581	0.1698
Kab. Pesisir Selatan	0.2080	0.4037	Kab. Pasaman Barat	0.1672	0.3848
Kab. Solok	0.2079	0.4208	Kota Padang	0.1912	0.5334
Kab. Sijunjung	0.2017	0.4580	Kota Solok	0.2279	0.2706
Kab. Tanah Datar	0.1510	0.7301	Kota Sawahlunto	0.1845	0.3735
Kab. Padang Pariaman	0.1855	0.5242	Kota Padang Panjang	0.1632	0.2141
Kab. Agam	0.2155	0.5450	Kota Bukittinggi	0.1992	0.4260
Kab. Lima Puluh Kota	0.1339	0.7470	Kota Payakumbuh	0.1417	0.6865
Kab. Pasaman	0.2212	0.2636	Kota Pariaman	0.1469	0.5800
Kab. Solok Selatan	0.2381	0.0287			

From Table 4, it is evident that model performance varies significantly across regions. Most districts exhibit RMSE values between 0.13 and 0.26, indicating moderate levels of prediction error in reconstructing contraceptive use. For instance, Kabupaten Lima Puluh Kota and Kabupaten Tanah Datar achieve the lowest RMSE values (0.1339 and 0.1510, respectively), accompanied by relatively high R^2 scores (0.7470 and 0.7301), suggesting a strong model fit in these areas. In contrast, several regions such as Kabupaten Solok Selatan ($R^2 = 0.0287$), Kabupaten Dharmasraya ($R^2 = 0.1698$), and Kota Padang Panjang ($R^2 = 0.2141$) show very low R^2 values, implying that the ST-PINN model explains only a small portion of the variation in observed contraceptive use. These low R^2 values, combined with relatively high RMSE, indicate that the model struggled to capture the temporal and spatial complexity in those regions or contextual heterogeneity not fully learned by the model. Some regions, such as Kota Payakumbuh (R^2=0.6865, RMSE = 0.1417) and Kab. Padang Pariaman (R^2 = 0.5242, RMSE = 0.1855) demonstrates intermediate performance, with moderately accurate predictions and reasonable variance explanation. Overall, while the ST-PINN framework shows promise in modeling spatial and temporal variation in contraceptive dynamics, the performance metrics reveal uneven predictive accuracy across districts.

These findings resonate with broader observations in spatial-temporal modeling literature. For example, studies benchmarking global vs. local spatial regression models demonstrate that global models often underperform in high spatial heterogeneity contexts, where localized patterns dominate [24], [25]. Similarly, hybrid machine learning approaches that integrate spatial heterogeneity control, such as combining Random Forest and CNN augmented with Moran's I, have shown significantly improved R^2 and reduced RMSE in prediction tasks [26].

3.4 Model Performance Evaluation

To evaluate model performance, RMSE and R^2 are used to quantify prediction accuracy and explanatory power. The performance comparison between models is presented in Fig. 9 (RMSE) and Fig. 10 (R^2). This comparison not only shows differences in prediction accuracy but also reveals the extent to which the model is able to capture spatial and temporal complexity in patterns of contraceptive use. The following presents a visual comparison between PINN and ST-PINN models based on two key evaluation metrics, RMSE and R^2.

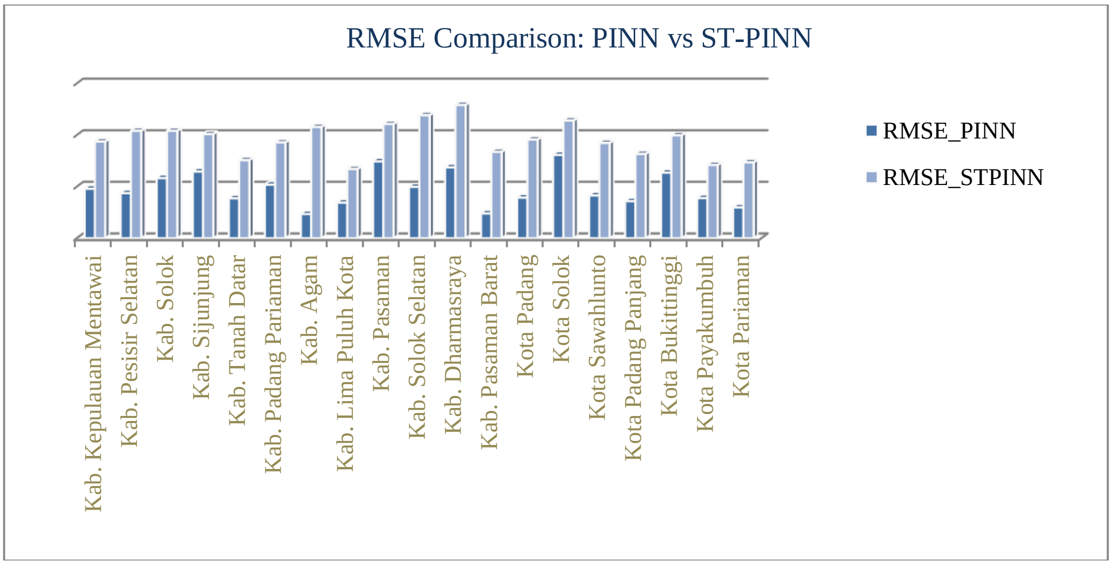


Figure 9. RMSE Comparison: PINN versus ST-PINN

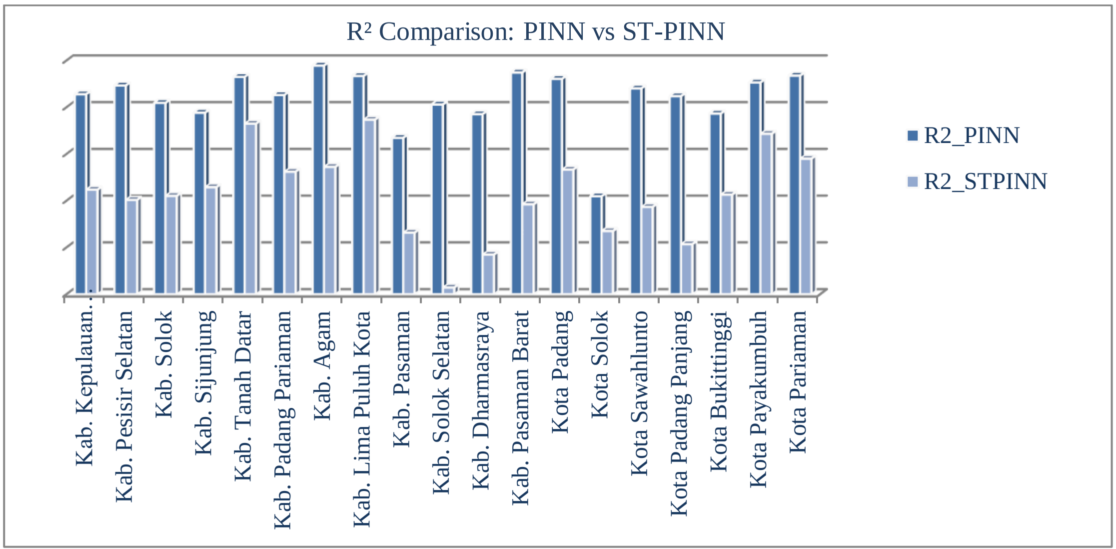


Figure 10. R^2 Comparison: PINN versus ST-PINN

As summarized and visualized in Fig. 9 and Fig. 10, the PINN model consistently outperformed the ST-PINN model across all districts and cities in West Sumatra Province in terms of both RMSE and R^2 values. Figure 9 illustrates the RMSE comparison, where the PINN model achieved substantially lower error magnitudes, ranging from 0.04678 in Kabupaten Agam to 0.16132 in Kota Solok, while the ST-PINN recorded higher RMSE values between 0.13388 (Kabupaten Lima Puluh Kota) and 0.25811 (Kabupaten Dharmasraya). Figure 10 presents the R^2 comparison, showing that the PINN model maintained generally high explanatory power exceeding 0.85 in most regions, including Kabupaten Agam (0.9785), Kota Pariaman (0.9355), and Kabupaten Tanah Datar (0.9302). In contrast, the ST-PINN model exhibited relatively weaker performance, with some districts such as Kabupaten Solok Selatan (0.0287) and Kota Padang Panjang (0.2141) displaying low R^2 values. These results suggest that while the ST-PINN framework effectively captures spatial variations in contraceptive dynamics, its predictive precision tends to decrease in regions characterized by irregular or noisy temporal patterns. Overall, the comparative findings affirm that the PINN model provides superior stability and temporal accuracy, whereas the ST-PINN contributes complementary insights into spatial heterogeneity, making both models jointly valuable for comprehensive analysis of spatio-temporal population dynamics. This comparison highlights a clear trade-off between predictive accuracy and the ability to model spatial heterogeneity. The PINN model prioritizes temporal accuracy and stability, resulting in lower prediction errors and higher goodness-of-fit, particularly in regions with consistent data patterns. In contrast, the ST-PINN framework sacrifices some predictive precision in order to incorporate spatial variability, enabling the identification of region-specific dynamics that are not captured by standard PINN models. Therefore, the two approaches serve complementary roles: PINN is more suitable for accurate prediction and model fitting, while ST-PINN provides deeper insights into spatial heterogeneity, making their combined use valuable for comprehensive spatio-temporal analysis.

The observed spatial heterogeneity aligns with previous studies highlighting the influence of socio-economic and accessibility factors on contraceptive use patterns. Despite strong performance in several regions, the model shows reduced accuracy in areas with low R^2 values, indicating that unobserved local factors such as cultural behavior and service accessibility are not fully captured. These results emphasize the importance of region-specific strategies in family planning programs, as uniform policies may not effectively address local variations.

4. CONCLUSION

This study addresses the limitation of conventional contraceptive modeling approaches that assume spatial homogeneity and time-invariant parameters, which restrict their ability to capture localized and evolving reproductive behavior dynamics. To overcome this limitation, this study proposes a Spatio-Temporal Physics-Informed Neural Network (ST-PINN) integrated with the SCNP compartmental model, enabling the estimation of key parameters, adoption rate, success rate, and failure rate as functions of both time and space. Unlike existing approaches that typically consider either temporal dynamics or spatial variation separately, the proposed framework simultaneously integrates mechanistic modeling and spatio-temporal learning, providing a more comprehensive representation of contraceptive behavior. The results indicate that the PINN model achieves higher predictive accuracy, characterized by lower RMSE and higher R^2 values in regions with stable data patterns, while the ST-PINN framework demonstrates enhanced capability in capturing spatial heterogeneity and identifying region-specific contraceptive dynamics. These findings demonstrate that the proposed approach extends existing demographic and epidemiological modeling frameworks by combining data-driven learning with physical constraints, thereby improving both interpretability and flexibility. The results also highlight the importance of incorporating regional heterogeneity into family planning policy design, as uniform strategies may not adequately address local behavioral differences. However, the model does not incorporate socio-economic and behavioral covariates, which may influence contraceptive dynamics in certain regions. Future research should integrate multi-source data and explore hybrid modeling approaches that combine PINN with spatial statistical or agent-based models to enhance predictive performance and policy relevance.

Author Contributions

Lely Kurnia: Conceptualization, Methodology, Formal Analysis, Data Curation, Writing-Original Draft, Software, Visualization. Nor Azah Samat: Conceptualization, Methodology, Validation. Mira Meilisa: Visualization, Writing-Review and Editing. All authors discussed the results and contributed to the final manuscript.

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Declarations

The authors assert that they possess no recognized competing financial interests or personal affiliations that might be perceived as influencing the work presented in this study.

Declaration of Generative AI and AI-assisted Technologies

Generative AI (ChatGPT) was used only to assist with language polishing and formatting consistency (e.g., wording improvements and uniform terminology). No AI was used to generate research content, perform analyses, or create or modify figures and tables. The authors reviewed the manuscript in full and remain fully responsible for its content.

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