Computation Models for Tsunami Wave Propagation using Extended Cellular Automata

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Abstract: -Using traditional models to simulate the propagation of large-scale tsunami waves leads to low accuracy and low efficiency. To ensure higher timing accuracy of tsunami wave spread, built an enhanced model that connects cellular automata with an existing model of tsunami waves. To determine the ideal time step value, our approach considers how time steps affect simulation accuracy. The spread of tsunami waves using a two-dimensional cellular automata model was used to test the model. Extending cellular automata (CA) models for tsunami wave propagation involves incorporating additional complexity and realism to better simulate the dynamics of these natural phenomena. The findings indicate that 1/4 of the time required for all of the cellular material to be traversed is the ideal time step for the tsunami wave spread global cellular automata simulation program. With a mean accuracy of 86.78% and a mean Kappa coefficient of 0.6443, this model demonstrated strong temporal and spatial consistency when compared to historical tsunami wave data from NOAA. Combining the Kappa coefficient with extended cellular automata (ECA) can be beneficial in various applications, particularly those involving classification tasks or spatial modeling. The earliest arrival tsunami wave spread can be predicted and simulated using this approach.

Key-Words: - Tsunami wave spread, simulation, Cellular automata, Homogeneous Ocean, Kappa coefficient, Rupture line , Travel time ,Extended Cellular automata.

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1 Introduction

1.1 Tsunami Wave Propagation

When compared to other natural disasters, tsunamis are not common. Research on tsunamis has gained impetus among Indian Ocean bordering nations including India, Sri Lanka, and Indonesia since the 2004 tsunami catastrophes. Underwater earthquake that causes a tsunami wave generated. When the train waves reach the coastal zone, they merge to generate a massive wave in the ocean.

In order to provide coastal residents with an alert, the tsunami waves are forecast using historical data on tsunami wave generation, and wave characteristics are examined. When a tsunami wave is predicted, people living close to the coast are evacuated.

Technology can be used to forecast the formation of tsunami waves in the ocean, warning those who live near the coast. The tsunami wave's speed is proportional to the ocean's depth. The bathymetry of the ocean under its surface determines how quickly waves rise and fall, [1], [2], [3].

Sensitivity to waves is caused by the way the ocean floor's shape affects the wave propagation velocity. As tsunamis draw closer to the coast, wave dynamics get more complex; therefore, more study into tsunami run-up is essential to the creation of precise tsunami hazard maps. The force of the tsunami manifests itself differently depending on the area destroyed; it can be classified as a local, regional, or distant (transoceanic) tsunami depending on how far it is from the source, [3], [4].

The water's density is taken to be constant in this system. The ocean flow's role is insignificant.

Both vertical and horizontal extensions are present in the ocean. In comparison to the vertical, the horizontally stretched ocean is greater. Since the fluid motion of the ocean is taken over a great distance, the vertical component of the motion is not stronger than the horizontal velocity. The spherical polar coordinates of longitude, latitude, and distance from the earth's center can be used to express the equation of motion of the ocean. This study uses Huygen's principle, which is dependent on position, time, velocity, and other characteristics, to model the propagation of tsunami waves, [5].

This paper's first portion introduces the use of Mathematical modelling and tsunami wave propagate in the Cellular Automata model and the advantages of Extended Cellular automata.

The development of the Algorithm and framework for tsunami wave propagation using Extended Cellular automata are covered in section 2.

Section 3 presents the analysis of historical tsunami events of the homogeneous ocean modules are examined and implemented using the Extended Cellular automata and the outcomes of their simulations results.

The paper is concluded in Section 4.

1.2 Mathematical Modeling

Modeling is a technique used to accurately analyze devices, reason about situations with constraints, and identify and choose features of real-world situations. It also illustrates structures symbolically using a set of rules.

The study of actual devices is described by mathematical modeling, which is the depiction of a system or natural phenomenon in mathematical terms. It is used in many different scientific fields and aids in the description of systems with situational features, as well as the identification of various components and issues with precisely predictable behavior solutions. Mathematical models use a wide range of mathematical topics, including calculus, dynamics, systems of equations, differential equations, statistics, cellular automata, and operational research .The behavior of tsunami waves in these systems is quantified by a mathematical model, which is then combined with the properties of tsunami wave propagation by a computer simulation technique to display the predicted behavior of the waves, [5].

1.3 Huygens Principle Growth Model of Tsunami Wave

It is believed that the sea has a flat surface and a steady wind and waves. Time is the primary criterion. The initial wavefront may move in a circular motion based on the requirements mentioned above for the wavefront from the focal point.

The wave's motion simultaneously spreads in two orthogonal directions. Energy is transferred from one wave position to another by the wave motion, [5].

1.4 Introduction to Cellular Automata

Families of discrete, deterministic mathematical systems that are both geographically and temporally discrete and have an intrinsically parallel mode of evolution are known as cellular automata. Originally presented by Von-Neumann in the early 1950s as basic models of biological self-reproduction, CAs are widely used as archetypal models for intricate systems and processes made up of numerous identical, straightforward, locally interacting constituents.

Because these systems may produce a wide range of intricate behavioral patterns from collections of relatively simple underlying principles, there has been a lot of interest in studying these systems over the years. Furthermore, they seem to capture a great deal of important characteristics of intricate cooperative self-organizing behavior in real-time systems.

Cellular automata are dynamic systems that function in discrete space and time on a uniform, regular grid, characterized by local interactions. A cellular automaton is defined by a grid with initial states and a set of rules for state transitions. Generally, cellular automata consist of four components, which can be represented as a *tuple* (X, S, N, f):

a) **X** denotes the cells, which are objects in any dimensional space, known as cellular space. In this space, each cell is represented as $x=(x_1, x_2, x_3, .., x_m)$,where m is the dimension of the space. Each cell has a neighborhood.

b) **S** is a nonempty finite set of states. Each cell can only be in one state at any given time from this set, denoted as $s \in S$. Strict cellular automata also require the state variables to be discrete.

c) **Neighborhood Template N** specifies that the state of any cell depends on the states and configurations of other cells in its neighborhood, n. In two-dimensional space, two well-known

templates are the von Neumann neighborhood and the 5-cell neighborhood.
d) **f** is the state transition function rule, [6].

1.5 Tsunami Wave Spread Model

The spread of a tsunami wave in the ocean is modeled using a 17x17 matrix. Figure 1 shows the representation of the tsunami wave model. Each cell in the matrix represents the conditions occurring within it. The possible states for each cell are denoted by the values 0, 1, and 2, indicating the condition of the wave in the cell. A value of 0 (Empty) means the cell is empty or has not been traversed by the wave. A value of 1 indicates that the cell contains a wave that has not yet been traversed. A value of 2 (Traversed) signifies that the cell contains a wave that has already been traversed. Figure 1 shows the Cell representation in 17 x 17 size matrices.

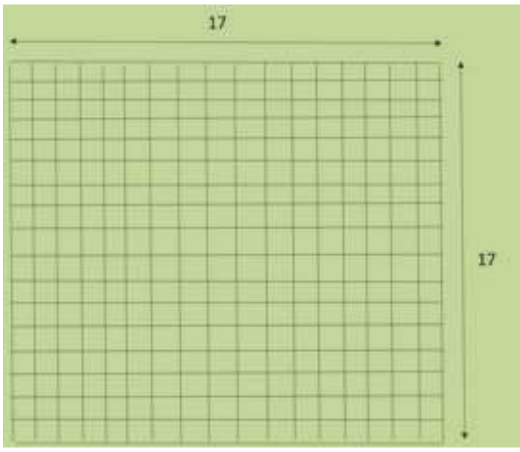

Fig. 1: Cell representation in 17x17 size matrices

The initial condition of the system offers two possibilities: traversed waves and untraversed waves. The presence of waves in a cell is indicated by the traversed state, while the opportunity for wave spread, if there is a wave in the cell, is represented by the traversing state. Thus, at the beginning of the simulation, the presence of traversed waves is denoted by the traversing state.

1.6 Von Neumann Neighborhood

Neighboring cells in a 2-dimensional form are represented using the Von Neumann Neighborhood. Neighboring cells are those located to the North, South, West, and East of a given cell. Each cell has four neighbors. Figure 2 represents Von Neumann Neighborhood's representation of a cell. A cell has neighbors to the North, South, West, and East.

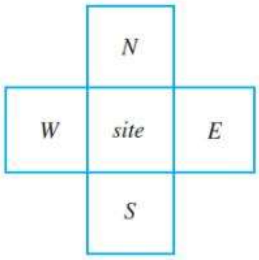

Fig. 2: Von Neumann Neighborhood's representation of a cell, [3].

The rule for the spread of tsunami waves based on the Von Neumann Neighborhood states that waves can traverse if their neighbors are traversed. Here's a paraphrased version of your description:
If a cell is empty (0) at time t, it remains empty (0) at time t+1. If a cell contains a wave (1) at time t, whether it remains a wave or traverses at time t+1 depends on whether neighboring cells have traversed waves. Cells marked as traversing (2) indicate that a wave is currently traversing out of the cell at time t, so at time t+1, the cell becomes empty (0).

The spread of tsunami waves adheres to rules that apply to every cell, including those positioned at the boundaries of the matrix. Cells located in the first and last rows, as well as the first and last columns, must interact correctly. To address this issue, boundary expansion is necessary by adding one or two cells at each boundary.

Figure 3 illustrates the model's geometry. Area A represents the observation area, a 17x17 matrix where each cell spans 80 km. Area B denotes the simulation area, and Region C specifies the area implementing the Periodic Boundary Condition. Figure 4 depicts how the Periodic Boundary Condition affects cells at the matrix boundaries, influencing corresponding cells on the opposite boundary. This iterative process is repeated 17 times.

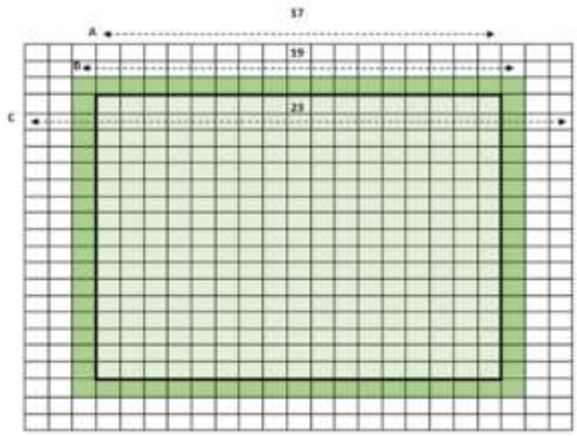
Fig. 3: Proposed Model Geometry

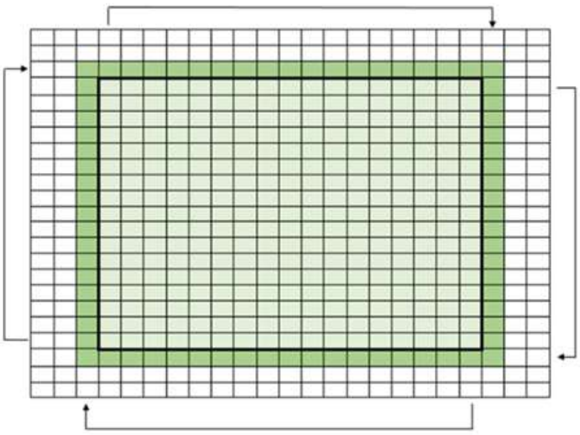

Fig. 4: Proposed Periodic Boundary Condition

For this modeling, locations from the eastern coastal region of India were selected, focusing on the 2004 Indian Ocean tsunami. Figure 5 depicts a the modeling study area focuses on the Indonesia subduction zone.

Figure 6 represents the modeling study area focuses on the Indonesia subduction zone located in the Indian Ocean.

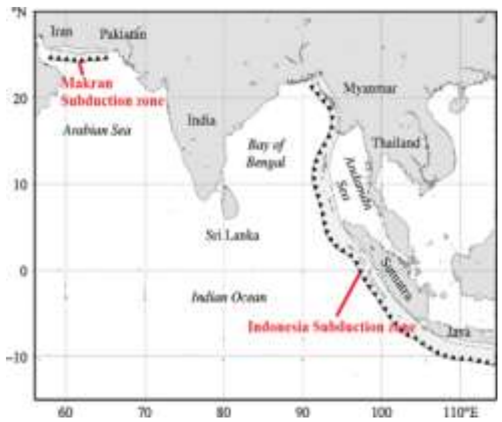

Fig. 5: The modeling study area focuses on the Indonesia subduction zone located in the Indian Ocean, [6]

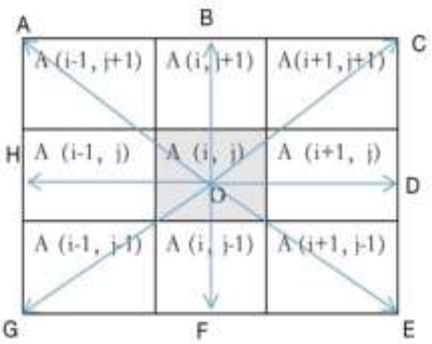

Fig. 6: These neighboring cells can be traversed by the i-cell, [7]

The cellular automaton is applied to the Moore neighborhood, a two-dimensional square lattice consisting of a central cell (the i-cell, which is the traversed one) and the eight cells surrounding it, as shown in Figure 6. These neighboring cells can be traversed by the i-cell. The spread of the tsunami wave is stochastically calculated, taking into account the directions between the center of the i-cell and the centers of the neighboring cells.

The tsunami wave propagates from a cell i to a neighboring cell j with a probability p_{ij} , referred to as the Tsunami Wave Spread Probability. The p_{ij} is influenced by factors such as the slope between the two cells, the wave effect (including direction and velocity), and the content of the j-cell. The probability p_{ij} of the tsunami wave spreading from the focal i-cell at time tk to a j-cell is calculated using the cumulative binomial probability formula [8], as shown in Equation (1):

$$p_{ij} = \left(1 - (1 - p_n)^{\alpha_{wh}}\right) \cdot e_m \tag{1}$$

where p_n is the nominal Tsunami Wave Spread Probability, a_{wh} is the factor that combines the topographic and wave influences on the probability, and e_m is the factor that simulates the effect of the homogeneous ocean.

1.7 Extended Cellular Automata

Through the use of an appropriate computer algorithm and theoretical tsunami wave spread models, computer simulations of tsunami wave propagation illustrate the occurrence and progression of a real tsunami wave through visuals or animation. Effective and precise simulations can assist managers in quickly estimating the propagation of tsunami waves, supplying a foundation for decision-making in the formulation of an efficient tsunami wave arrival time. The behavior of tsunami waves is a complicated mathematical and physical process. Numerous studies have demonstrated that the Richter scale value, ocean depth, wave speed, dip angle, and wave direction are the primary elements influencing the propagation of tsunami waves

Extended cellular automata (ECA) are a type of cellular automaton that extends the classical rules of Conway's Game of Life or other similar systems. While traditional cellular automata operate on a grid with cells that change state based on simple rules and the states of neighboring cells, extended cellular automata introduce additional complexity by allowing cells to have more states, interact with multiple neighbors, or follow more sophisticated rules.

These extensions enable ECA to model more complex phenomena and behaviors, such as simulating fluid dynamics, traffic flow, and biological systems. ECA has applications in various fields including computer science, physics, biology, and sociology, where they are used to study emergent behavior and patterns arising from simple local interactions among cells or agents, [9] advantages of Extended Cellular automata as compared to cellular automata, [9].

Extended cellular automata (ECA) offer several advantages compared to traditional cellular automata (CA), especially in the context of modeling complex systems and phenomena. Here are some key advantages:

1. Increased Complexity: ECA allowsfor the incorporation of additional attributes, variables, and rules compared to traditional CA. This increased complexity enables more realistic simulations of systems with diverse behaviors and interactions, making ECAs suitable for modeling a wide range of phenomena, from natural processes to social dynamics.

2. Dynamic Rules: Unlike traditional CA, which often have fixed transition rules, ECA allowsfor dynamic rules that can evolve over time or adapt to changes in the environment. This flexibility enables ECAs to capture emergent behaviors, feedback loops, and nonlinear dynamics more effectively, leading to richer and more accurate simulations.

3. Multi-scale Modeling: ECA can simulate phenomena across multiple spatial and temporal scales simultaneously, making them well-suited for modeling complex systems that exhibit hierarchical structures or interactions at different levels of organization. This capability enables researchers to study phenomena ranging from microscopic interactions to macroscopic patterns and trends.

4. Adaptive Behavior: ECA models can exhibit adaptive behavior, where the rules and behaviors of individual cells or agents change in response to local conditions or global trends. This adaptive behavior allows ECAs to self-organize, adapt to changing environments, and exhibit emergent properties that may not be apparent from the individual rules alone.

5. Parallelization and Scalability: ECA models can be parallelized efficiently and scaled to run on high-performance computing platforms. This scalability enables researchers to simulate large-scale systems with millions of cells or agents, allowing for more detailed and comprehensive analyses of complex phenomena, [10].

2 Development of Algorithm

For each time step, every cell in the domain is characterized by a state chosen from a finite set.
Specifically, each cell can be in one of three states:

- State 0 corresponds to cells where the tsunami wave has already traversed in previous simulation steps.
- State 1 corresponds to cells that are tsunami wave untraversed but may traverse in future simulation steps.
- State 2 corresponds to cells that are currently traversing the tsunami wave during the current simulation step.

The state transitions occur as follows:

- An untraversed cell (State 1) can transition to a traversing cell (State 2) with a probability determined by simulation parameters, or it may remain untraversed.
- A traversing cell (State 2) transitions to a traversed cell (State 0) after one-time step with certainty (probability equals 1).
- A traversed cell (State 0) remains unchanged and cannot transition to another state.

When a tsunami wave propagates from one cell to another, the latter is assigned a specific time $\Delta_t$for the wave to completely traverse it, as detailed further in subsequent sections. Once this time elapses, the cell changes its state from untraversed (State 1) to traversing (State 2), and then attempts to propagate the tsunami wave to adjacent untraversed cells. Operationally, the computed time step $S_k$for this state change is scheduled by a scheduler managing the tsunami wave propagation mechanism within the cellular automaton. Figure 7 represents the state diagram of the automata.

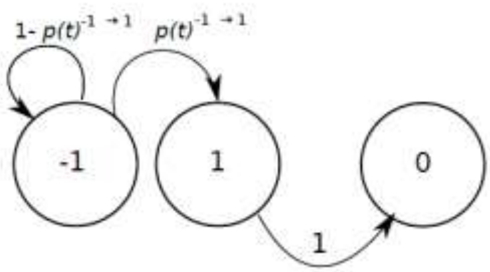

Fig. 7: The state diagram of the automata. States 1, 1, and 0 stand for untraversed cells, traversing cells and traversed cells, respectively. At a given time t, an untraversed cell has a probability, [5]

$P(t)^{1\to1}$ to tsunami wave traverse . Such probability is given by the overall state of the stochastic realization, initial, and boundary conditions. At the subsequent time step of the stochastic process, every traversing cell is going to be set to a traversed cell (and thus inactive).

The tsunami wave propagation is modeled as a contamination process between adjacent cells, with the spreading probability $P_{i,j}$ calculated from the tsunami wave spread probability P_n , modified by factors like ocean type, wave vector, and ocean depth. The evolution in time combines the nominal wave spread velocity $V_n$and the influencing factors via a RoS model. For each cell, the model calculates the probability u (x_p,t) of being traversed at time t and space x, based on numerous stochastic simulations (N=100). This is summarized in Figure 7.

The 2004 Indian Ocean tsunami, triggered by a massive underwater earthquake off Sumatra on December 26th, was the 9.2-magnitude earthquake from Sumatra to the Andaman Islands, covering 1200 km. Figure 8 shows the study area, including the epicenter, rupture boundary, and specific locations selected for detailed investigation.

Fig. 8: Model study area of the Indian Ocean zone, [6]

The tsunami wave propagates outward as a cylindrical wave in eight directions (N, NE, E, SE, S, SW, W, NW). To reduce computation time, the direction is chosen based on desired locations for the earliest tsunami arrival. For the 2004 Indian Ocean tsunami, the NW direction was chosen to focus on India's coastline.

Figure 9 shows a general iterative scheme of the CA model, with a flexible and probabilistic neighborhood relationship R_k , where expansion occurs only by infected cells. Wind direction θ and power ρ guide propagation, ensuring a realistic simulation. Uncertainties are accounted for using a Bernoulli random variable B_e(ρ) to determine cell infection. This approach is summarized in Figure 4 with an example.

The summarized approach is illustrated in Figure 9: starting from a grid state (S_k) with only the central element infected, infection probabilities are calculated for each cell using θ and ρ. The update criterion (U_k) based on random draws determines the next state (S_{k+1}). Figure 10 shows the Cellular automata discrete time step of the proposed model

This model's key contribution is estimating infection probabilities through a stochastic update criterion, functioning as a Monte Carlo method, with the law of large numbers estimating event frequencies for each cell and generation, [11], [12].

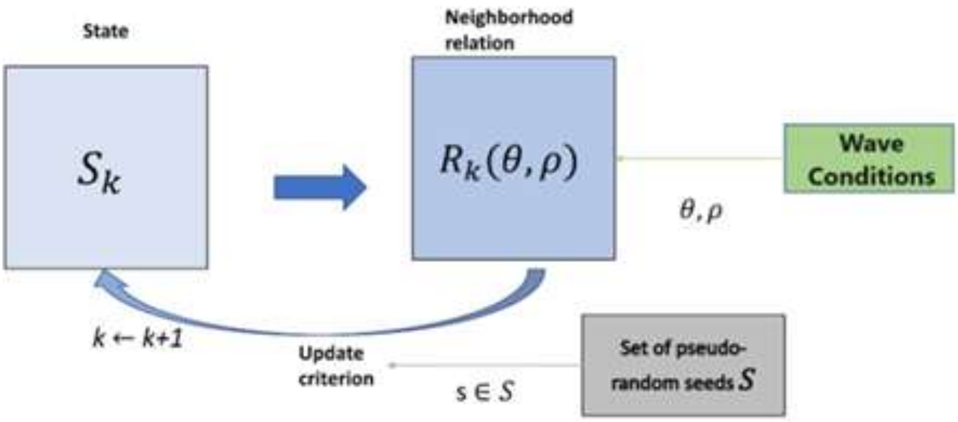

Fig. 9: The operational principles of the proposed model

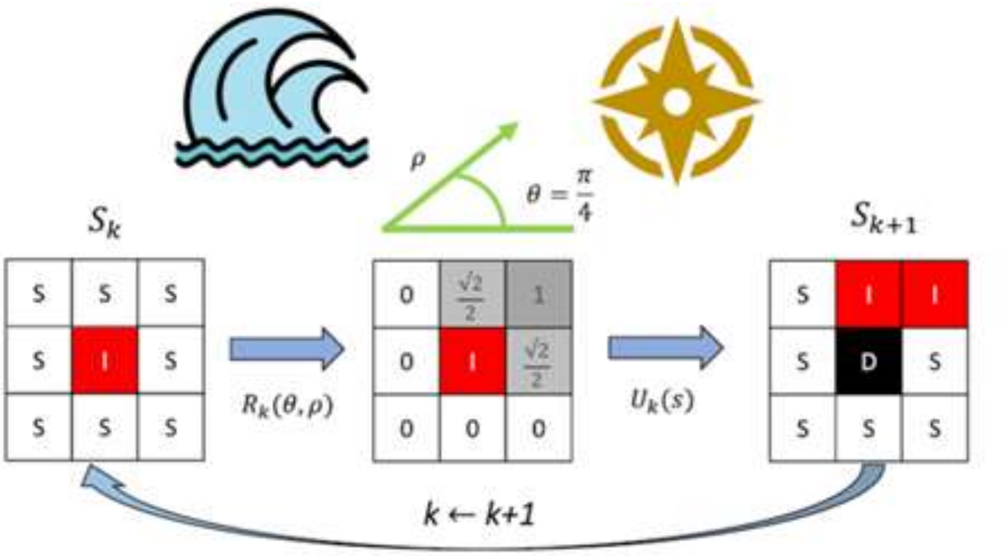

Fig. 10: Cellular automata discrete time step of the proposed model, [13]

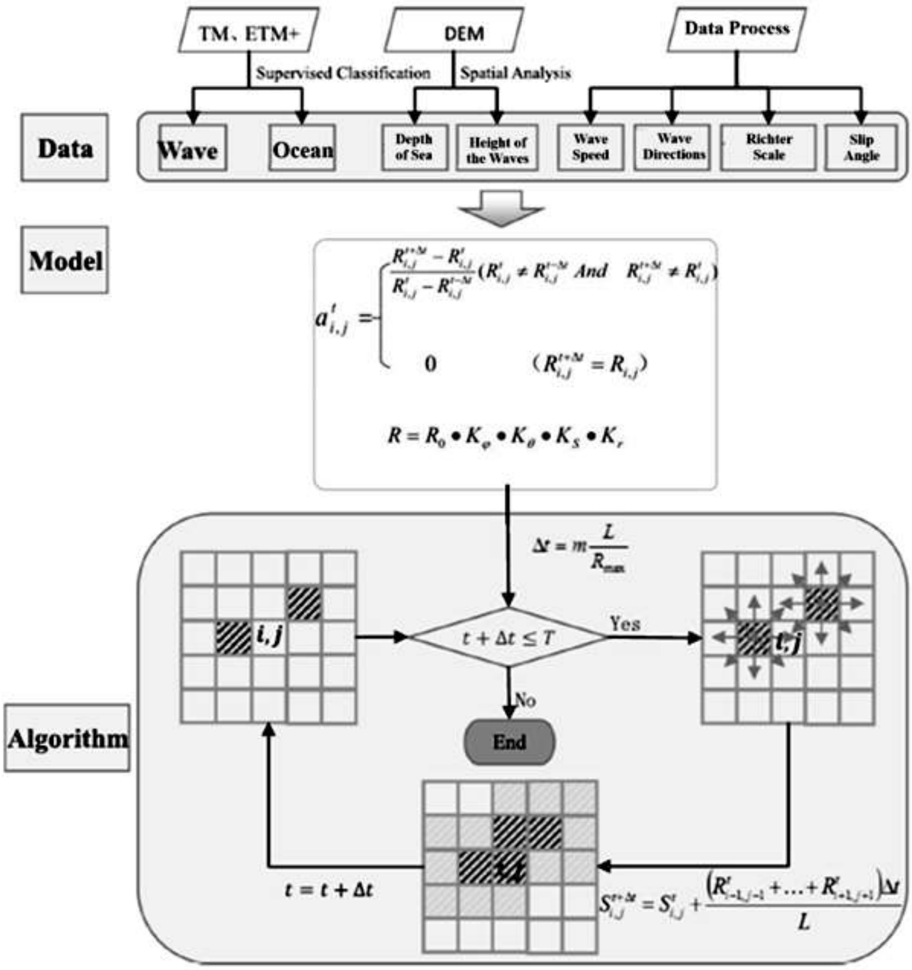

Fig. 11: Geographic Extended cellular automaton-based tsunami wave simulation spread algorithm design

There are three components to this algorithm for dispersing tsunami waves:: (1) Generation of tsunami wavesin the ocean, (2) Propagation model, and (3) algorithm implementation by coupling CA with the improved model shown in the Figure 11.

2.1 Data Description

The poorer efficiency of traditional tsunami wave propagation simulations can be attributed to their comparatively higher input parameter count. Images and historical data from tsunami warning stations were chosen as source data for this investigation. Downloaded from the National Centers for Environmental Information is Climate Data Online (CDO).

Using the highest likelihood approach, the study region was divided into homogenous ocean, depth of sea, Indian Ocean, wave height, and beachfront area data and photos. This two-step procedure is required to obtain a more realistic outcome when simulating tsunami wave processes and to lessen inaccuracies brought on by varying spectral characteristics.

2.2 The Algorithm of Geographic Cellular Automata

According to cellular automata rules for a specific discrete time evolution, cellular automata are dynamic systems defined in cellular space by the cellular discrete finite-state composition.< n-dimensional cellular space, the state, the number of neighbors, and state transition rules> [(i.e., < Z^n, *S*, *N*, *f*>)] are some ways to characterize it, [13].

The geographic cell space (Z^n) in the tsunami wave spread geographic CA algorithm is made up of units with various geographic combustion circumstances (S). The state of each cell varies with discrete time, dependent on its own state as well as the state of Moore neighbors units (N), where the state transition rules $S^{t+\Delta t} = f(S^t, N)$imprise the system's core. This is in accordance with the laws (f) of tsunami wave spread.

Therefore, this tsunami wave spread CA algorithm uses an80 km grid image of the study area as the cell space, where the pixel value represents the cell state. Assuming S is the state of the cell, it can be described as follows:

Consequently, the cell space for this tsunami wave spread CA technique is a 30-m grid image of the study area, where the pixel value denotes the cell state. If S represents the cell's state, it can be explained as follows: S = 0 (initial condition – no disturbance in the sea), S = 1 (initial tsunami wave traversed), S = 2 (full traversed, has the ability to traverse sur-rounding cells), S = 3 (traversing) or S = 4 (traversed).

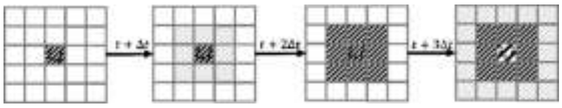

Fig. 12: Method for altering the cellular state

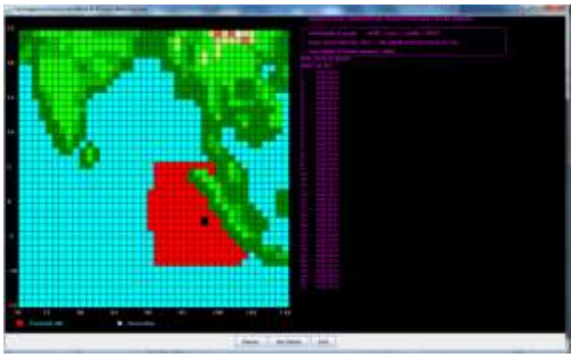
Fig.13: Typical view of the Color indication of simulation results with eight topography conditions

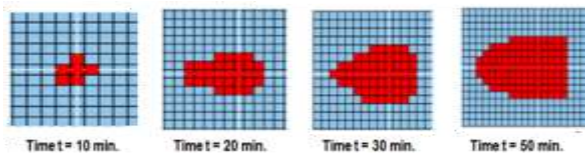

Fig. 14: Homogeneous Ocean, Horizontal Wave Motion with Secondary Wave Front in North-West

Cells with a state of 2 will constantly transit neighboring cells after entering information about the tsunami wave and its duration, hence controlling the spread of the wave. Time evolves in a discrete way, meaning that the tsunami wave's state at any given moment (Δt) may be determined based on the wave state at that time (t), following a time step of t+Δt.

The state transition rule is designed based on actual tsunami wave procedures from early traversing to traverse. In the algorithm, if the state of a traverse cell is 0 (S = 0, un traversed) and there exists S = 1 in neighborhood cells, then the cell value at the next time can be calculated by Eq. (2). If S = 1 at this time (early traversing), then S will become 2 (full traversing) at the next moment. If S = 2 and the states of neighborhood cells are equal or larger than 2 or are not traversable, then S = 3 (traversing gradually). If S = 3 at this time, then the state of the cell will be S = 4 at the next moment (completely traversed).

The Cell (i, j) is the focal point of the tsunami wave in the cellular state change process shown in the Figure 12, which propagates across nearby cells at a specific speed at time $t + \Delta t$ At time $t + 2\Delta t$, neighborhood cells go from early traversing to complete traversing, at which point cell (i, j) starts to travel. At time t+3Δt, neighborhood cells moved through their own neighborhood cells at a specific speed.

Figure 13 represents typical view of the Color indication of simulation results with eight topography conditions. (In this approach, assume that changing from one state to another takes the same amount of time).

Figure 14 shows the simulation output of Homogeneous Ocean, Horizontal Wave Motion with Secondary Wave Front in North-West.

The following equations can be used to represent this process:

$$S_{i,j}^{t+\Delta t} = S_{i,j}^{t} + \frac{\left(R_{i-1,j-1}^{t} + \ldots + R_{i+1,j+1}^{t}\right)\Delta t}{L}\left(R_{i,j}^{t} = 0\right) \quad (2)$$

$$\Delta t = m\,\frac{L}{R_{max}} \qquad (m < 1) \quad (3)$$

where (i, j) are the cell's column and row numbers, which indicate the cell's location; Δt is the time step; t is the current time; and $t + \Delta t$ is the next moment; The following moment's state of cell (i, j) is represented by $S_{i,j}^{t+\Delta t}$;

The pace of spread from the neighborhood cell (i - 1, j 1) is given by $R_{i-1,j-1}^{t}$ at time t to the center cell; L = 150 is the cell size; m is the step size factor; the higher the value, the lower the simulation accuracy and the higher the algorithmic efficiency; and R_{max} is the maximum spreading speed (R_{max} and Δt vary based on the time and environmental variables).

3 Algorithm Implementation

The Java programming language has been used for the simulation model and the cellular automata paradigm to create the tsunami wave spread simulation system.

3.1 Data Process

To develop our simulation model, In the initial stage a two-dimensional cellular automata tsunami wave propagation model was developed, and implement the data to improve the accuracy result and data was taken from NOAA, [14].

3.2 Optimal Time Step and Time Correction Coefficient

The tsunami wave spread speeds were fixed in order to examine the effects of a time step on the tsunami wave spread simulation. With a focal point serving as the initial source of the tsunami, the wave should propagate outward in concentric circles. For the formula$\Delta t = m\,\frac{L}{R_{max}}$, the step size m was set to 0.01, 0.03, 0.1, 0.125, 0.3, 0.5, 1.0, and 1.2 by R_{max}.

Figure 15 demonstrates the results that the analog graph approaches a circle extremely closely when m is 0.125. Even though the step size was extremely small, the simulation result did not get more round when m = 0.01, 0.03, or 0.1.

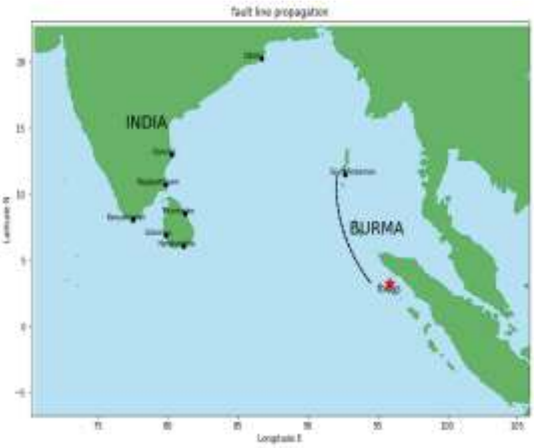

Fig. 15: Simulation result obtained of Rupture line towards north from epicenter approximately 1400 km

Table 1. 2004 Tsunami Event Information, [15]

Event Information	Values
Date	26-12-2004
Time	58 min 53.4 sec –UTC
Location	Indonesia-Sumatra-Aceh-Off West Coast
Epicenter	95.854 ^{0}E, 3.316 ^{0}N
Magnitude	9.1

Table 1 depicts 2004 Tsunami Event Information. To reduce computation time, the method predicts the earliest arriving tsunami wave direction. In this study, the coastline of India, located northwest of the tsunami's origin, is analyzed. The results show the tsunami wave spread towards India over various time intervals, indicating it took 2.5 hours to reach the Indian coastline and 2 hours to hit Sri Lanka's coastline, [16].

3.3 Discussion

Following the formulation of the model, simulations were conducted to study the spread of tsunami waves in the ocean using the Cellular Automata method. The simulations involved varying the traverse probability, which denotes the likelihood of a tsunami wave spreading. The traverse probability values used were 10%, 20%, 30%, 40%, 50%, 60%, 70%, and 80%. For each traverse probability value, the simulation was iterated 17 times.

Figure 16 presents the simulation results for a 10% wave traverse probability. It shows limited wave propagation, primarily near the focal point source. The percentage of ocean area traversed by the tsunami wave at this probability is 0.34602%. At a 20% traverse probability (not detailed in the provided text), the traversed area percentage is 0.69024%. Figure16 displays the results for a 30% wave traverse probability, where more extensive wave propagation is observed. The percentage of ocean traversed by the tsunami wave at this probability is 1.0381%. Figure 16 depicts the simulation results for a 40% wave traverse probability, indicating further spread of the tsunami wave.

The model determined that the ideal step size was m = 0.125. The denominator is 8 for m = 0.125 = 1.0/8.0, indicating that eight neighborhood cells contributed to the combustion of the central cell. Reduced m has more negative effects on the findings than positive ones. For instance, when multiplied by 1.0/16.0, accuracy increases, but the method quickly becomes less efficient due to the multiplicity of cycles for all cell state values in the research region.

The findings also demonstrate that the tsunami wave propagates excessively swiftly in the absence of the time correction factor (Kt = 1).

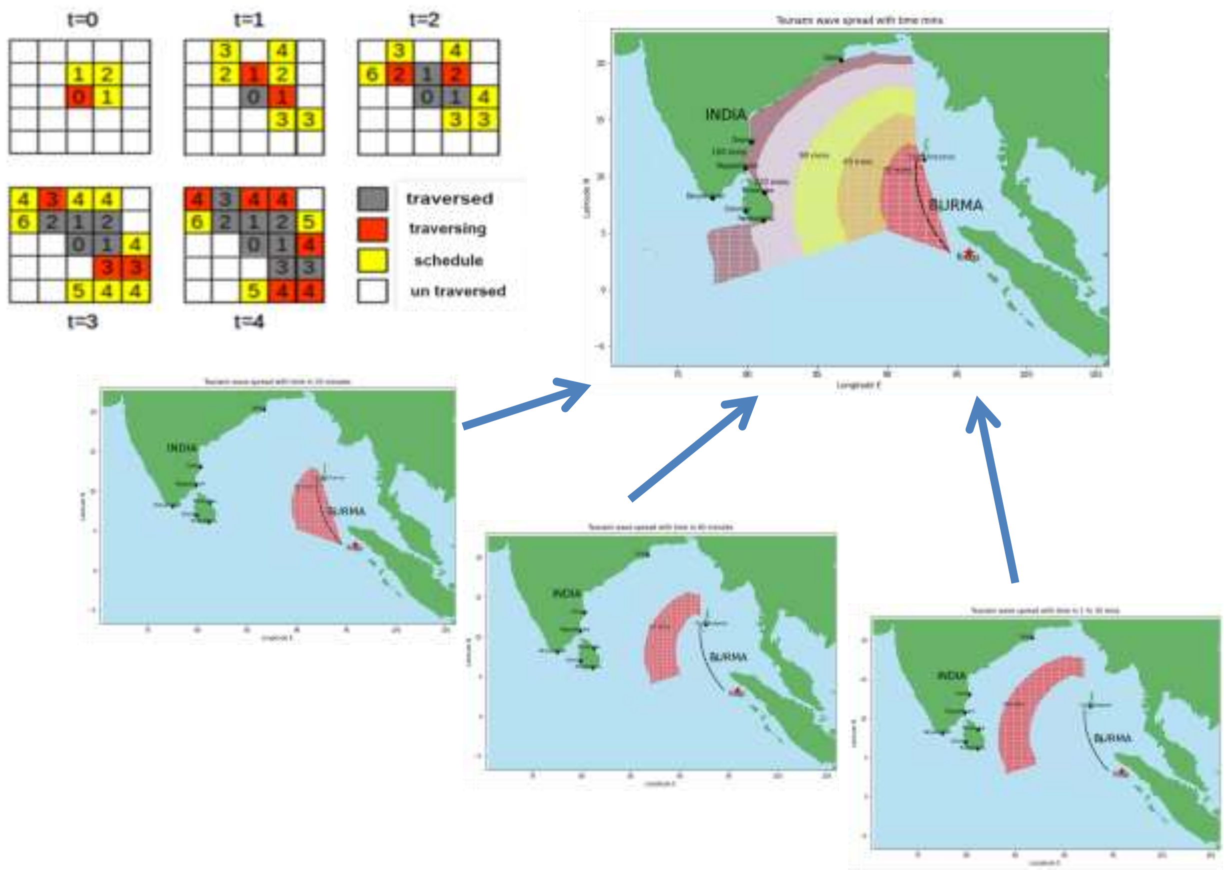

Fig. 16: Simulation result obtained of the modeling study area of Extended Cellular automata in the 2004 Off West Coast of Sumatra earthquake

3.4 Simulation Results and Accuracy

The initial tsunami wave's outcomes at the coastline of the destinations in the 2004 Sumatra tsunami. Figure 17 represents the simulated wave extent in the tsunami wave of the homogeneous ocean.

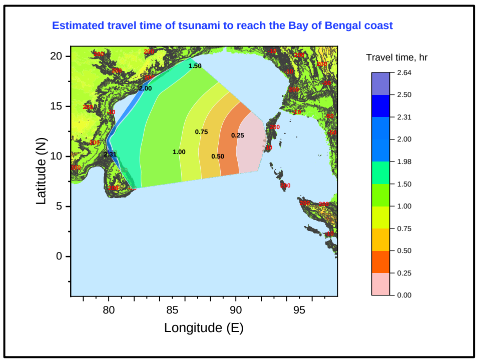

Fig. 17: Simulation result obtained Travel time of tsunami wave to reach the coast of Bay of Bengal

The connection between historical and estimated tsunami travel times to reach defined locations from the 2004 Sumatra earthquake tsunami is illustrated in Table 2. The table indicates a very slight, potentially inconsequential discrepancy between historical and estimated tsunami wave heights near the shore, which can be addressed in the future. The average percentage accuracy of estimated values is calculated as 94.65 %. Figure 18 represents the earliest arrival time of tsunami wave spread comparison with the actual time of the Extended Cellular automata model.

Table 2. Comparison graph between the historical and estimated tsunami wave travel time of three models to reach the destinations due to the 2004, Sumatra earthquake-tsunami

S.No	Name of the Location	OTT (hrs)	2D CA Model [27]	Interactive CA Model [28]	Extended CA Model ETT (hours)	Accuracy (%)
1	Chennai	2.567	2.257	2.319	2.437	0.949357
2	Cuddalore	2.31	2.02	2.062	2.18	0.943723
3	Velankanni	2.51	2.24	2.262	2.38	0.948207
4	Nagapattinam	2.516	2.206	2.268	2.386	0.948331
5	Karaikal	2.27	1.96	2.022	2.14	0.942731
6	Vizag	2.6	2.29	2.352	2.46	0.946154
7	Paradeep, Orisa	2.46	2.15	2.212	2.33	0.947154

Here,
OTT – Original Travel time
ETT –Estimated travel time

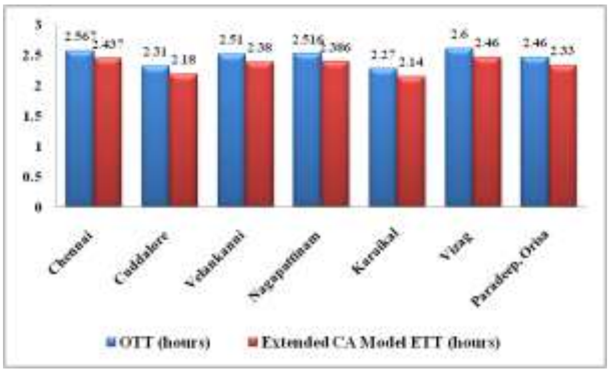

Fig. 18: The Earliest arrival time of tsunami wave spread comparison with actual time

4 Conclusions

This Extended Cellular automaton model introduced an enhanced technique for simulating tsunami wave propagation. The construction of the algorithm considered its broad applicability, ease of data acquisition, and configurable parameter sets. The study tackled the issue that a fixed time step, as used in traditional CA algorithms, may constrain decision-makers ability to formulate practical plans. A novel adaptive tsunami wave spreading simulation algorithm was developed, which integrates with a two-dimensional Cellular Automata model.

This algorithm accounts for various tsunami wave factors and the dynamic homogeneous ocean environment by creating a speed change rate index that adaptively adjusts the time step.

This ensures that the simulation adapts to complex real-world scenarios, offering more detailed insights into tsunami wave propagation as the wave navigates through different conditions while maintaining simulation accuracy.

The following four key justifications for the use of cellular automata are ranked in increasing order of theoretical significance:

1. The simulation's findings demonstrate how closely the spread of tsunami waves in a homogenous ocean matches those of real tsunami waves. Efficiency and accuracy are both high, as evidenced by the Kappa coefficient of 0.6443 and mean accuracy of 94.65 %.
2. The model may be improved in the case of tsunami meteorological data; specifically, the efficiency and accuracy of simulation results could be increased by optimizing the cell automaton time step and tsunami wave model correction. The Kappa coefficient involves interpreting their implications for the reliability, consistency, and overall performance of the model or classification system in the context of the study

3. By fine-tuning the time step and time correction coefficient, the simulation results were enhanced by comparing the observed and simulated tsunami wave spread.

Declaration of Generative AI and AI-assisted Technologies in the Writing Process

During the preparation of this work the authors used Grammarly for language editing. After using this service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

- Syed Mohamed has carried out the following:

- Identified the parameters
- Developed the theory and performed the computations.
- Verified the analytical methods
- Developed the theoretical formalism, performed the analytic calculations and performed the numerical simulations
- Carried out the statistical, mathematical, computational techniques to analyze the historical and study data.
- Carried out the simulation and the implementation using Extended Cellular Automata.
- Designed the model and the computational framework and analysed the data
- Carried out the implementation

- Chithirai Pon Selvan M has carried out the following:

- Encouraged
- Helped suggestion given in the articles

Both authors contributed to the final version of the manuscript

Sources of Funding for Research Presented in a Scientific Article or Scientific Article Itself

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Conflict of Interest

The authors have no conflicts of interest to declare