FORESHADOWING Regional Connectivity

Exploratory Tool for Enhancing Southeast Asia Connectivity

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Abstract

Prior to commencing a construction for a rail network, feasibility studies are conducted. These studies include terrain analysis, identifying surrounding population clusters, weather conditions and even environmental considerations. A significant number of investments, resources, and labour are dedicated to this rigorous pre-selection process.

Given the geographical and socio-political challenges native to Southeast Asia—ranging from unique terrains to fragmented governance— and the political risks associated with large infrastructure projects, incorporating a data-driven calculator into the pre-selection process can increase engagement to underserved regions, maximise structure longevity and have greater consideration towards sustainable infrastructure planning, while weighing the risks specific to Southeast Asia—all of which are keys in the potential realisation of such hypothetical connectivity projects.

This project aims to develop a rail routing calculator for the general public, primarily rail enthusiasts, to route train lines and determine station placements with conditions specific to Southeast Asia. Instead of focusing solely on economically dominant areas, this "what-if" scenario helps bring attention to neglected regions by leveraging data such as ground elevation and earthquake safety distances and propose a few options of varying strengths of rail routes from Point A to Point B, which are then weighted against a final, feasibility score that is computed based on its constituent criteria.

In the tool, the use of interactive mapping is the centerpiece of this visualisation. Users will input an origin and a destination which can be controlled by adjusting the value of the indexes, which ultimately amend the route drawn on the map. Elaborative details regarding the results will be published on a dashboard with the indexes tabulated. A PDF export will make it possible to save the result for future reference.

As the hypothetical routes are determined by actual datasets and built into algorithms with condition specific to Southeast Asia, this will give insights to non-natives about the realities of planning projects of such scale in this region, as such a tool is usually reserved for experts of this field. This conceptualisation helps to promote inclusive development in underserved regions as someone who lives in rural areas can now visit cities readily, highlighting the advantages of enhanced connectivity within a region, while of course, not forgetting the importance of not cutting down too many trees while doing so.

Disclaimer

Given the multidisciplinary nature and numerous expertise involved—engineers, urban planners, environmental scientists and policymakers, in projects of such scale, it is prudent to note that this visualization will serve as a hypothetical planning tool that democratize access to information necessary to its realisation. This would allow the public to explore different possibilities and simulate outcomes based on varying parameters (e.g. environmental factors, or population needs), while considering factors and challenges specific to Southeast Asia.

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1 Introduction

1.1 Costs of Infrastructure Projects in Southeast Asia Context

Historically, Southeast Asia has struggled to develop cohesive transport networks due to natural barriers, political fragmentation, and economic disparities, which has contributed to poor urban planning and underutilized transport routes. Such pan-regional infrastructure generally requires substantial amount of funding, time and resources.

The region's terrain, ranging from rainforests to river deltas along with its weather, characterized by monsoon seasons and high humidity—introduces new challenges to the durability and maintenance of existing infrastructure as deterioration through flooding and high humidity, has led to a necessity for frequent maintenance work and in return, their associated costs.

One of the keys to making these projects worthwhile; maximizing their utility within their limited shelf life; is to place more emphasis on the quality and inclusiveness of its planning — to get as many Southeast Asians onboard as possible.

1.2 Project Scope

This project, inspired by the rapid urbanization and infrastructure challenges in Southeast Asia, where uneven development has led to economic disparities and access to resources, aims to develop a data visualization-based calculator that seeks to democratize civil projects in regards to public transport lines and station placements planning across Southeast Asia.

One of the key challenges amongst infrastructure projects is public perception—many believe such projects are too ambitious, complex or costly to execute. This calculator we will develop uses combinatorial optimization—called the “slime mold” as it is a natural organism known for its efficient network-building capabilities. In the name of biomimicry, this concept is applied in this context; to propose the most sensible curvature of a rail network to be constructed, demonstrating that infrastructure planning is "not as hard as we think," even in natural disasters prone environments like Southeast Asia, where factors such as tsunami can significantly impact planning doctrine.

By visualizing these factors, the tool weighs the risks and challenges specific to Southeast Asia to assist in routing train lines and determine station placements and gauges the likelihood of the realisation of such hypothetical connectivity projects.

Historically, the focus on rail way expansion has always been solely on economically dominant areas. This "what-if" scenario helps bring attention to neglected regions and propose a few options of “Best Fit Curve”, each with their own varying strengths of rail routes from Point A to Point B, which are then weighted against a final, feasibility score that is computed based on its constituent criteria. By incorporating data and deriving its results, this not only allows a more inclusive infrastructure planning but also translates to the eventual ease of movement for human capital, services, and resources, facilitating economic integration in Southeast Asia.

1.3 Contextualization with Existing Frameworks

Various regional frameworks share similar objectives in enhancing trade, connectivity, and infrastructure development. The African Continental Free Trade Area (AfCFTA) Transport Infrastructure Development initiative aims to improve intra-African trade by improving transport infrastructure across the continent, namely the land, sea and air links. This framework uses GIS spatial analysis, cost-benefit analysis, and multi-criteria decision-making (MCDM) to optimize planning and allocation of investments (African Union 2020). Similarly, the ASEAN Connectivity Master Plan (ACMP) covers beyond roads and railways, which also include IT, digital infrastructure and energy, aiming to improve Southeast Asia's institutional, physical, and digital connection. This initiative leverages GIS for corridor mapping, network optimization models, and scenario planning to achieve its objectives (ASEAN Secretariat 2016).

On a global scale, China's Belt and Road Initiative (BRI) facilitates international trade by investing in the construction and expansion of roads, railways, ports, and also investing in developing energy, and telecommunications infrastructure. This framworks employs combinatorial optimization and GIS-based spatial analysis to maximize efficiency in infrastructure development (World Bank 2019). Similarly, North America's NAFTA/USMCA Transport Corridors framework optimises road, rail, and maritime transport networks to improve trade between the United States, Mexico, and Canada.Effective transportation planning is supported by the use of simulation-based optimisation, GIS for corridor analysis, and traffic flow modelling (U.S. Department of Transportation 2020).

Infrastructure integration is a focus of other regional organizations, such as the Pacific Alliance infrastructural Integration Initiative, which uses GIS for network optimisation and assessing economic impact, promoting economic development through connectivity between Chile, Colombia, Mexico, and Peru (Pacific Alliance 2018). In South Asia, the SAARC Regional Multimodal Transport Study seeks to develop a multimodal transport system using GIS for corridor identification, multi-modal network optimization, and cost-effectiveness analysis (SAARC Secretariat 2014). Meanwhile, the Trans-European Transport Network (TEN-T) aims to create a seamless transport network across EU member states by incorporating combinatorial optimization, GIS for spatial planning, traffic simulation models, and lifecycle cost analysis (European Commission 2021). These frameworks collectively demonstrate the significance of data-driven planning techniques in achieving regional and global connectivity goals.

1.4 Contextualization with Existing Methodologies

Some concepts deemed relevant in approaching this brief include Combinatorial Optimization, where through branches of Network Optimization Models, which are mathematical models used to design, analyze, and improve networks by weighting different factors such as cost, efficiency, and level of connectivity, and Urban Network Analysis (UNA), an approach in analyzing the structure of urban networks, such as roads and transit systems. These are combined to determine the most suitable solution(s) within their respective scenarios. This approach is crucial in urban planning, where resource allocation and network efficiency are key indicators of model city plans (Ahuja, Magnanti, and Orlin 1993). Similarly, Geographic Information Systems (GIS) plays a crucial role in spatial analysis, translating those analysis to visualizations to enable policy makers to make data-driven decisions regarding infrastructure planning (Longley et al. 2015).

Another framework of interest will be Multi-Criteria Decision-Making (MCDM), which helps to prioritize projects based on key factors, such as labour cost, social impact, and technical feasibility. By evaluating these criteria, planners can weight all the odds before implementing policies (Belton and Stewart 2002). In tandem, Traffic Flow Modeling and Simulation helps to optimize traffic patterns through a simulation of various traffic scenarios, allowing a clear assessment of the impact of different transport medium before its actual implementation (Daganzo 1997).

Finally, Climate-Resilient Infrastructure Frameworks ensure that infrastructure development incorporates long-term sustainability and resilience. With greater availability of the range of impact of natural disaster caused by extreme weather events, this helps urban planners minimize risks and enhance durability of their plans (Hallegatte, Rentschler, and Rozenberg 2019). These combined methodologies create a comprehensive foundation for developing sustainable and efficient urban infrastructure.

2. Treatment

2.1 Data Types and Collection

Terrain Data:

- **Ground Elevation:** Digital elevation models (DEMs) and LiDAR for terrain and topography. https://opentopography.org/
- **Historical Earthquakes:** Seismic data to spot earthquake hot zones. https://earthquake.usgs.gov/
- **Historical Tsunami:** Records of historic tsunamis to determine safety distance away from coastlines. https://www.ngdc.noaa.gov/hazard/tsu_db.shtml
- **Forested Areas:** Green forested cover to annotate conversation zones and mapped to evaluate environmental impact. https://globalforestwatch.org/
- **Coastlines:** Shapefiles for coastal mapping. https://www .openstreetmap.org/
- **Humidity:** Climate datasets for humidity levels. https://climateknowledgeportal.worldbank.org/
- **Biodiversity Indicators:** Datasets on protected areas and species distribution. https://data.unep-wcmc.org/

Census Data:

- **Population Counts:** Demographic data to spot high-density areas. https://human-settlement.emergency.copernicus.eu/
- **Land Area:** Geospatial data as a base for overlaying other data. https://www.naturalearthdata.com/
- **Economic Activity**: Economic data to identify high-demand areas. https://data.worldbank.org/ / https://www.oecd.org/en/data.html / https://data.adb.org/

Miscellaneous:

- **Existing Network:** Point/Line shapefiles on roads, railways to assess connectivity and avoid redundancy and repetition of new lines on existing networks. https://data.opendatasoft.com/pages/home/

2.2 Weighing Indexes Specific to the Southeast Asian Climate

A set of indexes are tabulated and weighted based on their relevance in Southeast Asia, creating prospective factors crucial in the potential realisation of hypothetical projects of such scale. For each index, a rubric is created in consideration of the constituting scores of each factor; $ie.\ (Elevation\ Score)$ if *Higher = Better*; if not, $ie.\ 1 -\ (Historical\ Tsunami\ Score)$ is used to invert the score and illustrate *Higher = Worse*. In each of these factors there are specific weights assigned, denoted by $ie.w(n)$ to depict the level of their emphasis within each index. Each factor has been normalized to a scale of **0 to 1**, where:

0 = Least favorable condition (high risk, low suitability).

1 = Most favorable condition (low risk, high suitability).

1 Tsunami Risk Index (TSI) – Overall Weightage: 20%

One of the factors in determining this index is the incorporation of a risk assessment of tsunamis, which involves the identification of tsunami sources, an analysis of historical events, and based on these, the modeling of potential tsunami scenarios. In addition, identifying the exposed populations, infrastructure and ecosystems is also essential in determining tsunami risk levels. The severity of tsunami impact depends on a few factors, namely coastal depth, land elevation, and the presence of natural barriers such as mangroves or coral reefs (IOC 2015).

Preprocessing - Standardization and Normalization

Starting with database cleaning and removing NaN values, other checks also include scanning for non-Latin symbols which may interfere with parsing of the data.

Standardise unit of measurement into the metric system and in this case, the Coordinate Reference System (CRS) as WGS84 and normalize the data to a range (Range of 0-1) to ensure interoperability and compatibility across different factors, ensuring equal influence on the final calculation. This is done using the Min-Max Normalization:

Formula: $X' = \frac{X - Xmin}{Xmax - Xmin}$, where X is the original value; X' is the normalized value; $Xmin$ is the minimum value, and $Xmax$ is the maximum value within the dataset.

Ground Elevation - Elevation Score - Weightage 20% of the 20%

The relationship between ground elevation and tsunami risk is straightforward—lower elevations face greater danger. Using Lidar data imported into CesiumJS, we reclassify terrain into three categories:

Low elevation (Below sea level or < 10 m above sea level) – Score < 0.33

Moderate elevation (10 m – 50 m) – Score ~ 0.34 - 0.66

High elevation (> 50 m) – Score 0.67 - 1.0

The Min-Max Normalization is used to scale elevation values between 0 (low risk) and 1 (high risk). However, since higher elevation is of less risk, we not invert this score as it remains directly proportional to feasibility.

$$Elevation\ Score = \frac{Elevation - ElevationMin}{ElevationMax - ElevationMin}$$

Distance from Coastlines - Coastline Proximity Score - Weightage 40% of the 20%

As tsunamis originate from the ocean, distance from the coastline plays a pivotal role in risk assessment. We can calculate the Euclidean distance from each location to the nearest coastline. Locations closer to the shore have a significantly higher risk, while those further inland have a lower risk.

Most tsunamis cause the most damage within the first **5 km** of impact. However, larger tsunamis have reached over 10 km inland in extreme cases (Jaffe et al. 2011). The 2011 Tōhoku earthquake and tsunami in Japan recorded runup distances of up to 6 km in some areas (Mori et al. 2012). According to Satake et al. (2008), tsunami waves in Southeast Asia have historically dissipated significantly beyond 5 km, making this a reasonable baseline for risk assessment.

> 10 km from Coast – Score ~ 0.67 - 1.0

5 - 10 km from Coast – Score ~ 0.34 - 0.66

0 - 5 km from Coast – Score < 0.33

The Min-Max Normalization is used to scale distances from the coast to between 0 (least favourable) and 1(most favourable). However, since a higher distance is safer, we do not invert this score as it is directly proportional to feasibility. 10 km serves as the upper normalization limit for this factor.

$$Coastline\ Proximity\ Score = \frac{Distance\ from\ Coastline - Xmin}{Xmax - Xmin}$$

Historical Tsunamis - Tsunami Prevalence Score - Weightage 40% of the 20%

Historical tsunami data is one of the key indicator of recurring risk. Some regions experience frequent tsunamis due to their proximity to tectonic plates. To quantify this, we gather historical tsunami event records from NOAA's Global Tsunami Database.

Studies indicate that most coastal areas within a 100 km radius of past tsunami events are vulnerable to future tsunamis (Okal and Synolakis 2008), the Indian Ocean Tsunami in 2004 caused damage over thousands of kilometers, but the most severely impacted areas were within 100 km of the tsunami-generating fault zones (Lay et al. 2005).

Using GIS, we map the frequency of tsunamis across a radius of **100 km** from the location of interest. The more tsunami events recorded in that area, the higher its risk score.

Few Tsunami Count – Score ~ 0.67 - 1.0

Some Tsunami Count – Score ~ 0.34 - 0.66

Frequent Tsunamis – Score < 0.33

The Min-Max Normalization is used to scale tsunami counts to between 0 (least favourable) and 1(most favourable). However, in this case, this value requires to be inverted, as a higher frequency indicates a unfavourability and is inversely proportionate to feasibility.

$$Tsunami\ Prevalence\ Score = 1 - \frac{Historical\ Tsunamis\ in\ 100\ km\ Radius - TsunamiMinwithinRegion}{TsunamiMaxwithinRegion - TsunamiMinwithinRegion}$$

Weightage [20-40-40] of the 20%

A **20-40-40** weight distribution is considered for the Tsunami Risk Index (TSI), with an Elevation Score of 20%, this is due to the fact that while higher ground offers protection, tsunamis can still penetrate inland, reducing its overall importance (Scheer et al. 2020). The Coastline Proximity Score is weighted at 40%, as tsunamis lose energy as they move further inland, making distance an important factor for risk assessment (Dominey-Howes et al. 2006). Historical Tsunamis (Tsunami Prevalence Score) stands at 40% weightage as an area that had once experienced tsunami is more likely for a tsunami to reoccur. (Berryman 2006).

Factors	Weightage
Elevation Score	20%
Coastline Proximity Score	40%
Tsunami Prevalence Score	40%

TSI Formula:

$$TSI = w1 \times (\, Tsunami\ Prevalence\ Score) + w2 \times (Coastline\ Proximity\ Score) + w3 \times (Elevation\ Score)$$

TSI Formula; with Weightage

$$TSI = 0.4 \times (Tsunami\ Prevalence\ Score) + 0.4 \times (Coastline\ Proximity\ Score) + 0.2 \times (Elevation\ Score)$$

Risk Category	Score (Min 0 - Max 1)	Interpretation
High Risk	0.00 - 0.33	• Frequent past tsunamis • Low elevation • Near the coast
Moderate Risk	0.34 - 0.66	• Occasional tsunami activity • Medium elevation
Low Risk	0.67 - 1.0	• No tsunami history • High elevation • Far from coast

2 Structure Durability Index (SDI) – Overall Weightage: 20%

In general, buildings located in close proximity to areas with high seismic activities should incorporate base isolation, energy dissipation devices, and reinforced structural components to withstand such events. Whereas structures built at higher elevations experience reduced risks of flooding, they are exposed to increased wind loads and geological instability from the ground.

It is also worth mentioning that coastal buildings face accelerated deterioration due to saltwater exposure, hence requiring extra consideration, such as having an alternative construction practice like the use of corrosion-resistant materials and elongated foundations to resist storm surges. Regions with high humidity levels result in a faster degradation of materials like wood and metal, hence it is necessary to employ moisture-resistant construction techniques and adequate ventilation (FEMA 2006).

Preprocessing - Standardization and Normalization

Starting with database cleaning and removing NaN values, other checks also include scanning for non-Latin symbols which may interfere with parsing of the data.

Standardise unit of measurement into the metric system and in this case, the Coordinate Reference System (CRS) as WGS84 and normalize the data to a range (Range of 0-1) to ensure interoperability and compatibility across different factors, ensuring equal influence on the final calculation. This is done using the Min-Max Normalization:

Formula: $X' = \frac{X - Xmin}{Xmax - Xmin}$, where X is the original value; X' is the normalized value; $Xmin$ is the minimum value, and $Xmax$ is the maximum value within the dataset.

Proximity to Seismic Zones - Seismic Safe Score - Weightage 40% of the 20%

Seismic activity is heavily concentrated along the edges of the tectonic plates. According to the United States Geological Survey (USGS), regions within 50 km of fault lines experience the most severe effects of earthquakes, often exceeding Peak Ground Acceleration (PGA) of 0.3 g, which poses a huge risk to structural stability. (USGS 2021). These waves die down significantly after reaching the 150 km mark from the epicenter, thus it is used as the upper limit for risk assessment. (Bommer et al. 2002)

The Federal Emergency Management Agency (FEMA 2021) classifies seismic risk based on distance from fault lines as follows:

> 150 km Away – Score ~ 0.67 - 1.0

50 - 150 km Away – Score ~ 0.34 - 0.66

0 - 50 km Away – Score < 0.33

The Min-Max Normalization is used to scale distance to seismic zones to between 0 (least favourable) and 1(most favourable). However, in this case, this value does not need to be inverted, as a greater distance indicates favourability and is directly proportionate to feasibility.

$$Seismic\ Safe\ Score = \frac{Distance\ to\ Fault\ Line - Xmin}{Xmax - Xmin}$$

Ground Elevation - Elevation Score - Weightage 25% of the 20%

Ground elevation plays a critical role in determining the stability and durability of structures, particularly concerning flooding, landslides, and foundation integrity. Areas near sea level or below experience higher risks of flooding and erosion, whereas elevated regions are more stable but may face other environmental challenges like landslides in the case of extreme elevations. Ground elevation is categorized based on height above sea level, which impacts structural vulnerability.

Low elevation (Below sea level or < 10 m above sea level) – Score < 0.33

Moderate elevation (10 m – 50 m) – Score ~ 0.34 - 0.66

High elevation (> 50 m) – Score 0.67 - 1.0

The Min-Max Normalization is used to scale elevation values between 0 (low risk) and 1 (high risk). However, since higher elevation is of less risk, we not invert this score as it remains directly proportional to feasibility.

$$Elevation\ Score = \frac{Elevation - ElevationMin}{ElevationMax - ElevationMin}$$

Distance from Coastlines - Coastline Proximity Score - Weightage 20% of the 20%

As tsunamis originate from the ocean, distance from the coastline plays a pivotal role in risk assessment. We can calculate the Euclidean distance from each location to the nearest coastline. Locations closer to the shore have a significantly higher risk, while those further inland have a lower risk.

Most tsunamis cause the most damage within the first **5 km** of impact. However, larger tsunamis have reached over 10 km inland in extreme cases (Jaffe et al. 2011). The 2011 Tōhoku earthquake and tsunami in Japan recorded runup distances of up to 6 km in some areas (Mori et al. 2012). According to Satake et al. (2008), tsunami waves in Southeast Asia have historically dissipated significantly beyond 5 km, making this a reasonable baseline for risk assessment.

> 10 km from Coast – Score ~ 0.67 - 1.0

5 - 10 km from Coast – Score ~ 0.34 - 0.66

0 - 5 km from Coast – Score < 0.33

The Min-Max Normalization is used to scale distances from the coast to between 0 (least favourable) and 1(most favourable). However, since a higher distance is safer, we do not invert this score as it is directly proportional to feasibility. 10 km serves as the upper normalization limit for this factor.

$$Coastline\ Proximity\ Score = \frac{Distance\ from\ Coastline - Xmin}{Xmax - Xmin}$$

Humidity Score - Weightage 15% of the 20%

Humidity, with prolonged exposure, contributes to the weakening of the structure integrity. Buildings located in regions with humidity levels above **80%** experience accelerated degradation, particularly in metal structures, wooden beams, and concrete surfaces. The American Society of Heating, Refrigerating, and Air-Conditioning Engineers (ASHRAE) establishes that 50% humidity as the threshold for material durability, with degradation risks increasing significantly at 80% and above (ASHRAE 2022).

Even that, levels above 75% accelerate corrosion rates in structural metals, particularly steel and reinforced concrete used in urban infrastructure. Tropical regions consistently exceeding 80% relative humidity experience severe deterioration in wooden frameworks, requiring extensive maintenance and material treatment (Camuffo 2019).

Low Humidity (< 50%) – Score ~ 0.67 - 1.0

Moderate Humidity (50% - 80%) – Score ~ 0.34 - 0.66

High Humidity (> 80%) – Score < 0.33

The Min-Max Normalization is used to scale humidity index to between 0 (least favourable) and 1(most favourable). However, since greater humidity is unconducive to man made structure, we invert this score as it is inversely proportional to feasibility.

$$Humidity\ Score\ =\ 1\ -\frac{Humidity\ \ -Xmin}{Xmax-Xmin}$$

Weightage [40-25-20-15] of the 20%

A **40-25-20-15** weight distribution is considered for the Structure Durability Index (SDI), with a Seismic Safe Score of 40%, as seismic activity causes the most significant structural damage, so it carries the highest weight (FEMA 2021). While elevation is a factor, modern engineering techniques are able to mitigate some risks, so it holds less weight than seismic activity (World Bank 2020). As for coastal exposure, it increases flooding and storm risk, but not all structures are susceptible to such risk from their direct exposure. (IPCC 2019). Humidity usually affects structure over the long term, so it has less immediate impact than seismic activity or flooding - coastline exposure (ASHRAE 2022).`

Factors	Weightage
Seismic Safe Score	40%
Elevation Score	25%
Coastline Proximity Score	20%
Humidity Score	15%

SDI Formula:

$$\begin{aligned}SDI\ &=\ w1\times(Seismic\ Safe\ Score)\ +\ w2\times(Elevation\ Score)\\&\quad+\ w3\times(Coastline\ Proximity\ Score)\ +\ w4\times(Humidity)\end{aligned}$$

SDI Formula; with Weightage

$$\begin{aligned}SDI\ &=\ 0.40\times(Seismic\ Safe\ Score)\ +\ 0.25\times(Elevation\ Score)\\&\quad+\ 0.20\times(Coastline\ Proximity\ Score)\ +\ 0.15\times(Humidity)\end{aligned}$$

Durability	Score (Min 0 - Max 1)	Interpretation
Poor Durability	0.00 - 0.33	• High seismic activity • Low elevation

		● High humidity
Moderate Durability	0.34 - 0.66	● Some seismic activity ● Moderate elevation ● Moderate humidity
High Durability	0.67 - 1.0	● Low seismic activity ● High elevation ● Low humidity

3 Environmental Impact Index (E2I) – Overall Weightage: 15%

The degradation of the environment poses significant risks to public health and overall well-being. Hence, implementing frameworks focusing on sustainable infrastructure development is essential to mitigate environmental impacts. Deforestation, agricultural expansion, and urbanization have contributed greatly to habitat destruction and increased greenhouse gas emissions (MA 2005).

Simulating economic development and regional connectivity in the traditional sense has invoked a paradox, the greater amount of effort placed in establishing regional connectivity to facilitate economic growth, the greater the destruction of the environment. Thus there is a need to strike a balance between these 2 key aspects.

Preprocessing - Standardization and Normalization

Starting with database cleaning and removing NaN values, other checks also include scanning for non-Latin symbols which may interfere with parsing of the data.

Standardise unit of measurement into the metric system and in this case, the Coordinate Reference System (CRS) as WGS84 and normalize the data to a range (Range of 0-1) to ensure interoperability and compatibility across different factors, ensuring equal influence on the final calculation. This is done using the Min-Max Normalization:

Formula: $X' = \frac{X - Xmin}{Xmax - Xmin}$, where X is the original value; X' is the normalized value; $Xmin$ is the minimum value, and $Xmax$ is the maximum value within the dataset.

Land Use Change - Weightage 55% of the 15%

A critical factor in assessing environmental impact, as the rapid urbanization, deforestation, and agricultural expansion have contributed to the destruction and changes in the climate. The assessment of land use change involves the use of satellite imagery to detect difference in land composition over a period of time. Using Change Detection Analysis in remote sensing, satellite data is compared using classification algorithms such as Normalized Difference Vegetation Index (NDVI) (Giri 2016). This method helps identify urban expansion, deforestation, and shifts in agricultural zones, which are then converted into percentage change values, then further classified into risk category.

Regions experiencing deforestation rates above 25% are classified as high risk. A 10 - 25% change indicate reversible impacts, while areas with minimal land use change (<10%) have a significantly lower environmental impact. (Hansen et al. 2013).

Land Use Change > 25% – Score < 0.33

Land Use Change 10 - 25% – Score ~ 0.34 - 0.66

Land Use Change < 10% – Score ~ 0.67 - 1.0

The Min-Max Normalization is used to scale land use changes to between 0 (least favourable) and 1(most favourable). However, since greater changes is unconducive to the environment, we invert this score as it is inversely proportional to feasibility.

$$Land\ Use\ Change = 1 - \frac{X - Xmin}{Xmax - Xmin}$$

Biodiversity Indicators - Biodiversity Score - Weightage 45% of the 15%

Biodiversity indicators measure species richness within a region, using data from conservation organizations such as the International Union for Conservation of Nature (IUCN) and NASA's Earth Observation Program.

Regions experiencing a species decline of more than 30% over two decades are categorized as high risk due to ecosystem destabilization. Moderate impact zones are those experiencing 10-30% species loss, while areas with minimal biodiversity decline (<10%) have lower risk (Butchart et al. 2010).

Species Density > 30% – Score < 0.33

Species Density 10 - 35% – Score ~ 0.34 - 0.66

Species Density < 10% – Score ~ 0.67 - 1.0

The Min-Max Normalization is used to scale species density to between 0 (least favourable) and 1(most favourable). However, since greater density is unconducive to environmental disruption, we invert this score as it is inversely proportional to feasibility.

$$Biodiversity\ Score\ =\ 1\ -\frac{X\ -Xmin}{Xmax-Xmin}$$

Weightage - [55-45] of the 15%

A **55-45** weight distribution assigned to this index for which Land Use Change taking up 55% as it has a higher direct impact on environmental degradation than biodiversity scores (IPCC 2021). While biodiversity degradation is a long-term concern, land use change has a more immediate impact (Cardinale et al. 2012).

Factors	Weightage
Land Use Change	55%
Biodiversity Score	45%

E2I Formula:

$$E2I\ =\ w1\times(Land\ Use\ Change)\ +\ w2\times(Biodiversity\ Score)$$

E2I Formula; with Weightage

$$E2I\ =\ 0.55\times(Land\ Use\ Change)\ +\ 0.45\times(Biodiversity\ Score)$$

Impact	Score (Min 0 - Max 1)	Interpretation
High Impact	0.00 - 0.33	• Significant land conversion • High biodiversity presence
Moderate Impact	0.34 - 0.66	• Some land conversion • Moderate biodiversity presence
Low Impact	0.67 - 1.0	• Minimal land conversion • Low biodiversity presence

4 Operability Index (OPI) – Overall Weightage: 25%

The effectiveness of disaster response relies heavily on how fast the first responders can reach affected populations and how close emergency services are to the disaster site. Hence, this is determined by the availability and accessibility of emergency services within a region. Thus, transportation networks should be designed to serve as many people as possible, ensuring that populations in disaster-prone areas remain connected to major cities, which usually have more comprehensive services, and hence are able to resume their daily lives.

While serving as much of the populace as possible, such network should also be situated at optimal elevations—above flood levels but not in excessively high terrain that impedes access while avoiding both extreme elevations and low-lying flood zones. They should also integrate seamlessly with existing networks, creating redundancy and ensuring accessibility in times of crisis by reducing the likelihood of a single point of failure (NASEM 2012).

Preprocessing - Standardization and Normalization

Starting with database cleaning and removing NaN values, other checks also include scanning for non-Latin symbols which may interfere with parsing of the data.

Standardise unit of measurement into the metric system and in this case, the Coordinate Reference System (CRS) as WGS84 and normalize the data to a range (Range of 0-1) to ensure interoperability and compatibility across different factors, ensuring equal influence on the final calculation. This is done using the Min-Max Normalization:

Formula: $X' = \frac{X - Xmin}{Xmax - Xmin}$, where X is the original value; X' is the normalized value; $Xmin$ is the minimum value, and $Xmax$ is the maximum value within the dataset.

Ground Elevation - Elevation Score - Weightage 24% of the 25%

Areas near or below sea level experience higher risks of flooding, and erosion whereas elevated regions are more stable but may face other environmental challenges like landslides and accessibility issues in the case of extreme elevations. In this case, this metric strikes a balance between these two, making it a critical factor for urban operability (Wang et al. 2021). Hence, elevation cannot be too high and yet must remain above flood-prone levels, the ideal range is set between 10-50m based on studies of flood impacts in urban regions. (Jonkman et al. 2005).

Undesirable Elevation (< 5 m or >50 m above sea level)

Sub-Optimal Elevation (5 m – 10 m)

Optimal Elevation (10 - 50 m)

A simple Min-Max Normalization will not work in this context, because elevations being too low (<5m) or too high (>50m) are undesirable. Instead, we can use a **Piecewise Scoring** function that assigns the highest score (1) to the optimal range (10-50m), lower scores to suboptimal ranges (5-10m), and zero (0) to undesirable ranges (<5m and >50m), as denoted below:

$$Elevation\ Score\ = \begin{cases} 0 & \text{if } X < 5\text{m or } X > 50\text{m} \\ \frac{X-5}{5} & \text{if } 5 \leq X < 10\text{m} \\ 1 & \text{if } 10 \leq X \leq 50\text{m} \\ \frac{60-X}{10} & \text{if } 50 < X \leq 60\text{m} \\ 0 & \text{if } X > 60\text{m} \end{cases}$$

Elevation <5m or >50m - Score 0

Elevation between 5-10m - Linear increase from 0 to 1

Elevation between 10-50m - Score 1

Elevation between 50-60m - Linear decrease from 1 to 0; transition to undesirable

Elevation >60m - Score 0

Existing Network - Weightage 28% of the 25%

Connectivity is measured based on road and rail density (United Nations 2020). Urban infrastructure development suggests that well-connected regions with ≥5 km/km² of road density have significantly better emergency response (World Bank 2020). In contrast, regions with <1 km/km² are considered underdeveloped in terms of accessibility, leading to operational inefficiencies in transport and logistics (UN-Habitat 2018). The score is calculated using the number of connections per unit distance:

$$Connectivity\ Score\ = \frac{Total\ Network\ Length\ (km)}{Region\ Area\ (km^2)}$$

Regions with high infrastructure density (>5 km/km²) ensure better operability, while areas below 1 km/km² have limited access (ADB 2019). The classification is as follows:

High Accessibility (> 0.5 km/km²) – Score < 0.33

Moderate Accessibility (0.1-0.5 km/km²) – Score ~0.34 to 0.66

Low Accessibility (<0.1 km/km²) – Score ~0.67 to 1.0

The Min-Max Normalization is used to scale road density to between 0 (least favourable) and 1(most favourable). However, since lower accessibility grants more value to the prospects of this new connectivity project, we invert this score as it is inversely proportional to feasibility.

$$Existing\ Network = 1 - \frac{NetworkDensity - NetworkDensitymin}{NetworkDensity\ max - NetworkDensity\ min}$$

Proximity to Urban Centers - Urban Proximity Score - Weightage 24% of the 25%

Proximity to urban centers has a huge impact on the operability of infrastructure and emergency response times (World Bank 2019). Regions closer to urban hubs have more efficient response times due to the proximity of first responders and better infrastructure availability (World Health Organization, 2021). Emergency services have optimal response times within a 15 km radius, while distances beyond 50 km significantly delay response efficiency (Eide et al. 2012). Based on this, the classification is as follows:

High Accessibility (< 15 km from urban center) – Score ~0.67 to 1.0

Moderate Accessibility (15 km - 50 km from urban center) – Score ~0.34 to 0.66

Low Accessibility (> 50 km from urban center) – Score < 0.33

The Min-Max Normalization is used to scale proximity distances to between 0 (least favourable) and 1(most favourable). However, since lower accessibility is not desirable to the realisation of the project, we need to invert this score as it is inversely proportional to feasibility.

$$Urban\ Proximity\ Score = 1 - \frac{X - Xmin}{Xmax - Xmin}$$

where X is the distance to the nearest urban center.

Population Counts - Population Density Score - Weightage 24% of the 25%

High-density areas above 5,000 people/km² require stronger operability, while those below 500 people/km² are less service-dependent (OECD 2021), with the classification as follows:

High Demand (>5,000 people/km²) – Score ~0.67 to 1.0

Moderate Demand (500-5,000 people/km²) – Score ~0.34 to 0.66

Low Demand (<500 people/km²) – Score < 0.33

The Min-Max Normalization is used to scale population density to between 0 (least favourable) and 1(most favourable). Since high density is a viable reason for the realisation of the project, we do not need to invert this score as it is directly proportional to feasibility.

$$Population\ Density\ Score\ = \frac{Density\ \ - Densitymin}{Densitymax - Densitymin}$$

Weightage - [24-28-24-24] of the 25%

A **24-28-24-24** weight distribution assigned with Ground Elevation, Proximity to Urban Centers, and Population Counts being set equally within the index is due to their comparable, though indirect, influence on operability and service demand but do not directly impact service delivery or emergency response times (United Nations 2020). Existing Network, however, is weighted higher due to its direct and significant impact on operability, as a well-developed network is critical for ensuring rapid emergency responses (World Bank 2020).

Factors	Weightage
Elevation Score	24%
Existing Network	28%
Urban Proximity Score	24%
Population Density Score	24%

OPI Formula:

$$OPI = w1 \times (Elevation\ Score)\ +\ w2 \times (Existing\ Network\ Score)$$

$$+ \ w3 \times (Urban\ Proximity\ Score) \ + \ w4 \times (Population\ Density\ Score)$$

OPI Formula; with Weightage

$$OPI = \ 0.24 \times (Elevation\ Score) \ + \ 0.28 \times (Existing\ Network\ Score) \\ + \ 0.24 \times (Urban\ Proximity\ Score) \ + \ 0.24 \times (Population\ Density\ Score)$$

Operability	Score (Min 0 - Max 1)	Interpretation
Low Operability	0.00 - 0.33	• Isolated • High elevation • Low accessibility, not emergency-ready • Low population
Moderate Operability	0.34 - 0.66	• Moderately connected • Moderate elevation • Medium accessibility • Average population
High Operability	0.67 - 1.0	• Well-connected • Low elevation • High accessibility, emergency-ready

5 Population-Economic Importance Index (PEI) – Overall Weightage: 20%

As the world's urbanised areas account for more than 80% of the global gross domestic product, the dispersion of economic activities from cities to the countryside plays a vital role in national and regional development. There is also a correlation between population growth and economic importance as fast-growing urban areas tend to attract more investments and talents which spur more innovations, making them focal points for economic progress.

When it comes to urban infrastructure and economic productivity, cities that invest the most in well-planned infrastructure and public services experience the greatest sustained growth and competitiveness on a global scale (United Nations, 2019).

Preprocessing - Standardization and Normalization

Starting with database cleaning and removing NaN values, other checks also include scanning for non-Latin symbols which may interfere with parsing of the data.

Standardise unit of measurement into the metric system and in this case, the Coordinate Reference System (CRS) as WGS84 and normalize the data to a range (Range of 0-1) to ensure interoperability and compatibility across different factors, ensuring equal influence on the final calculation. This is done using the Min-Max Normalization:

Formula: $X' = \frac{X - Xmin}{Xmax - Xmin}$, where X is the original value; X' is the normalized value; $Xmin$ is the minimum value, and $Xmax$ is the maximum value within the dataset.

Population Counts - Population Density Score - Weightage 35% of the 20%

Raw population counts do not fully capture the population's spatial distribution, as large regions with lower densities might appear more important than smaller, high-density urban areas. Therefore, population density (people per km²) is used instead of raw population figures (OECD 2021). To ensure compatibility across datasets, population data is standardized to correct discrepancies due to different census collection periods or methodologies (United Nations 2019).

Research by Angel et al. (2011) indicates that urban centers with densities above 5,000 people/km² are considered high economic impact areas, while regions below 500 people/km² are generally considered low economic impact zones. Based on these thresholds, the three-tier classification follows:

High Economic Importance (> 5,000 people/km²) – Score ~ 0.67 - 1.0

Moderate Economic Importance (500 - 5,000 people/km²) – Score ~ 0.34 - 0.66

Low Economic Importance (< 500 people/km²) – Score < 0.33

The Min-Max Normalization is used to scale population density to between 0 (least favourable) and 1(most favourable). Since greater density is correlated to economic importance, we do not need to invert this score as it is directly proportional to feasibility.

$$Population\ Density\ Score = \frac{Density - Densitymin}{Densitymax - Densitymin}$$

Land Area - Land Area Normalised - Weightage 25% of the 20%

Land area normalization ensures that smaller regions with dense populations are not overshadowed by larger but sparsely populated areas. Large areas do not necessary indicate economic significance unless they are densely populated or economically active (World Bank 2022).

To tackle this, we can apply log transformation to reduce the skewed effect of excessively large regions in the index (Smith et al. 2018).

$$Normalized\ Land\ Area = \frac{log(X)\ - log(Xmin)}{log(Xmax) - log(Xmin)}$$

where X represents the land area of the region in km², and Xmin/Xmax represent the smallest and largest regions in the dataset.

GDP Per Capita Score - Weightage 40% of the 20%

GDP per capita, a primary indicator of economic prosperity, reflects the average income within a region. It is adjusted for inflation and purchasing power parity (PPP) to allow for meaningful cross-country comparisons (OECD 2022).

According to World Bank (2022), regions with GDP per capita above $40,000 USD are considered high-income and economically significant, whereas those below $5,000 USD are classified as low economic impact zones. Based on this, the classification follows:

High Economic Importance (> $40,000 USD) – Score ~0.67 to 1.0

Moderate Economic Importance ($5,000 - $40,000 USD) – Score ~0.34 to 0.66

Low Economic Importance (< $5,000 USD) – Score < 0.33

The Min-Max Normalization is used to scale GDP per capita to between 0 (least favourable) and 1(most favourable). Since greater per capita is correlated to economic importance, we do not need to invert this score as it is directly proportional to feasibility.

$$GDP\ Score = \frac{X\ - Xmin}{Xmax - Xmin}$$

where X is the GDP per capita of a region, and Xmin/Xmax represent the lowest and highest GDP per capita values within the dataset.

Weightage - [35-25-40] of the 20%

A **35-25-40** weight distribution assigned to this index for which Population Density taking up 35% as density directly influences economic activity and service demand

(OECD 2021). In addition, Land Area alone contributes **modestly** to economic significance compared to population density and GDP (Smith et al. 2018). Therefore, land area is assigned a 25% weight within the Population-Economic Importance Index to prevent bias toward large but economically inactive regions. Since GDP per capita directly reflects economic viability, it carries the highest weightage (8% of the 20%) in the Population-Economic Importance Index (World Bank, 2022).

Factors	Weightage
Population Density Score	35%
Land Area Normalised	25%
GDP Per Capita Score	40%

PEI Formula:

$$PEI = w1 \times (Population\ Density\ Score) + w2 \times (GDP\ Per\ Capita\ Score) + w3 \times (Land\ Area\ Normalised)$$

PEI Formula; with Weightage

$$PEI = 0.35 \times (Population\ Density\ Score) + 0.40 \times (GDP\ Per\ Capita\ Score) + 0.25 \times (Land\ Area\ Normalised)$$

Importance	Score (Min 0 - Max 1)	Interpretation
Low Importance	0.00 - 0.33	• Sparse population, • High level of economic activity
Moderate Importance	0.34 - 0.66	• Balanced population and economic activity
High Importance	0.67 - 1.0	• High population density • Low level of economic activity

2.3 Final Feasibility Index (FFI)

In this context, the 5 constituent indexes are combined, forming a new index which determines the score of the route from Point A to Point B. The goal is to minimise construction effort (ie. distance, terrain difficulty) while maximising regional connectivity, economic impact, and population engagement. The value here states how well the route adheres to identified constraints such as geographical hazards, population coverage, and structural resilience as the algorithm avoids areas prone to flooding or tsunamis.

The Final Feasibility Index is an index that aggregates and integrates all 5 indexes into a single score:

1. **Tsunami Risk Index** (Hazard Vulnerability)
2. **Structure Durability Index** (Structural Resilience)
3. **Environmental Impact Index** (Environmental Sustainability)
4. **Operability Index** (Overall Usefulness)
5. **Population-Economic Importance Index** (Economic and Demographic Value)

Weightage in Final Feasibility Index (FFI)

The weightage assigned to each of the 5 indexes in the **Final Feasibility Index** is based on its significance when it comes to the feasibility of the route.

The Tsunami Risk Index (TSI), Population-Economic Importance Index (PEI), and Structure Durability Index (SDI) are all weighted the same due to an equal emphasis on safety and prioritization serving the majority of the population, which is essential for long-term viability (Jonkman et al. 2005).

The Operability Index (OPI) is weighted the highest as it directly affects the functionality and accessibility of the area, with access to emergency services being critical to its success as a conduit (OECD 2020). The Environmental Impact Index (E2I) is weighted the lowest as environmental sustainability is crucial but less immediately impactful in the operational aspects of such connection (World Bank 2020).

In the **FFI**, the higher the value, the more feasible the project.

FFI Formula:

$$FFI = w1(TSI) + w2(SDI) + w3(E2I) + w4(OPI) + w5(PEI)$$

FFI Formula; With weightage

$$FFI = 0.20(TSI) + 0.20(SDI) + 0.15(E2I) + 0.25(OPI) + 0.20(PEI)$$

Index	Weightage
Tsunami Risk Index (**TSI**)	20%
Structure Durability Index (**SDI**)	20%
Environmental Impact Index (**E2I**)	15%
Operability Index (**OPI**)	25%
Population-Economic Importance Index (**PEI**)	20%

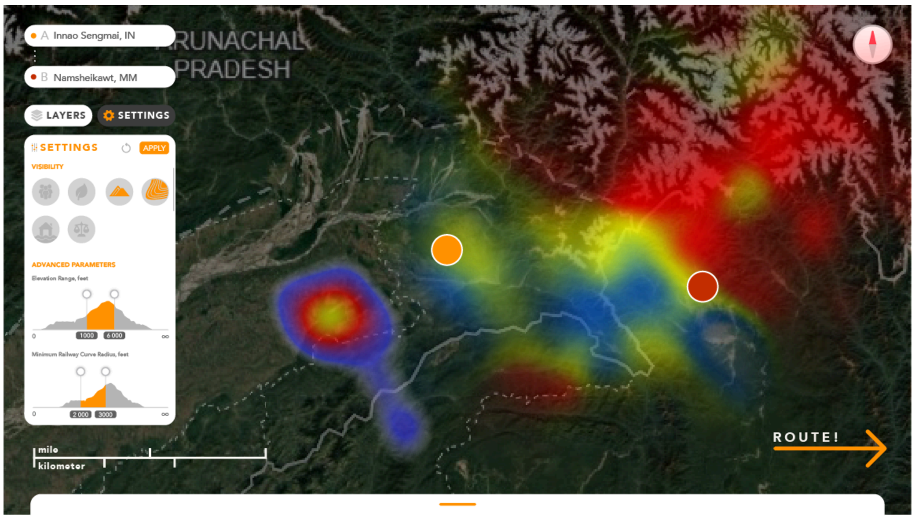
FFI Scoreboard

Feasibility	Final Score (Min 0 - Max 1)
Low Feasibility	0.00 - 0.33
Moderate Feasibility	0.34 - 0.66
High Feasibility	0.67 - 1.0

2.4 Visualization and Interpretation

2.4.1 Mockup and Prototype

The results are visualized using interactive network graphs, allowing users to explore the proposed network. Key features incorporated include:

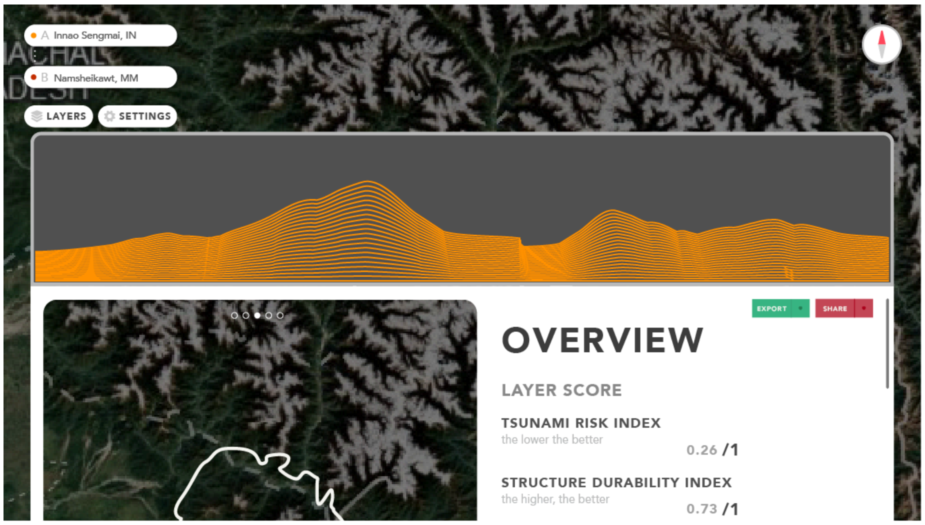


- Optimal rail lines and station placements that maximize accessibility and economic impact while minimizing exposure to potential risks.
- Index value settings to amend the final result.
- Interval distances / population density threshold for station placement.

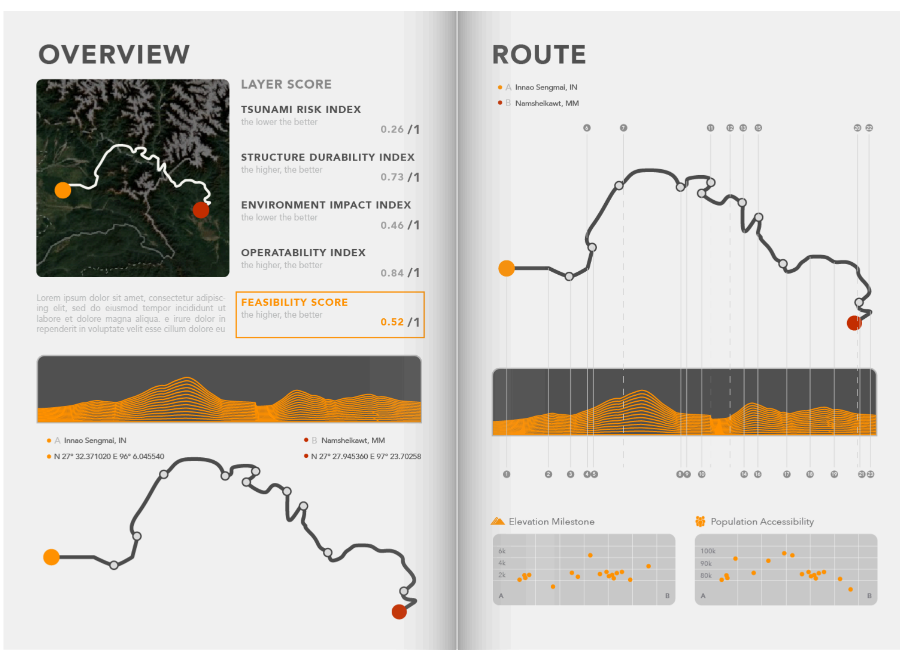
- The projected benefits of the project, one route for each strength:

- 1. Reduced travel time
- 2. Improved personal safety
- 3. Greater accessibility to specific regions.

- Terrain Cross Section



- Annotation on additional infrastructure required for project realisation ie. bridge, tunnel



2.4.2 Final Visualization - Trains, Lanes, and Data Grains

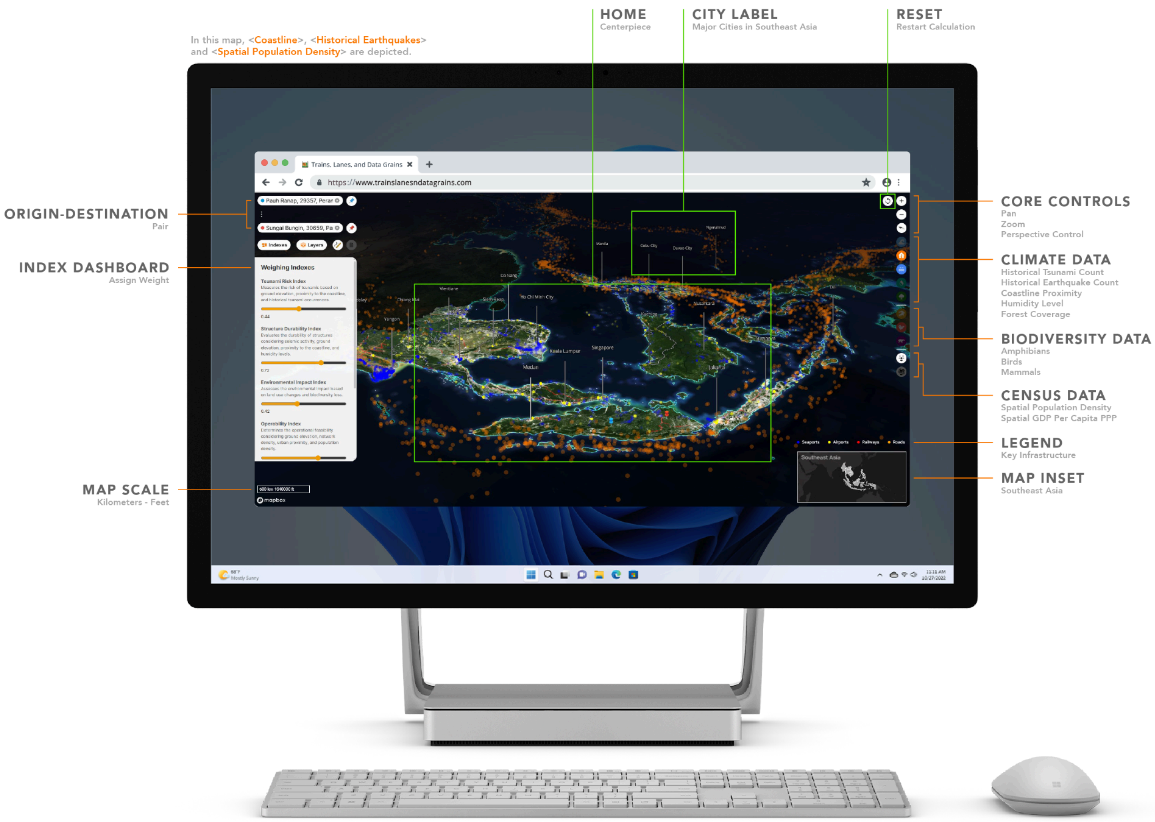
Trains, Lanes, and Data Grains, a speculative exploratory urban planning engine designed for activists, policymakers, and city planners looking to shake things up. Forecasting rail connectivity development in Southeast Asia, this tool is like SimCity meets real-world infrastructure—except the stakes are higher.

By transforming biodiversity and census data into hypothetical "What-if" scenarios, it reveals indiscernible pathways through challenging terrains and natural hazards like earthquakes. Whether advocating for underserved communities or optimizing railway routes, users can explore how data-driven urban futures can reshape regional connectivity.

What if you could find the best-fit route that maximizes services to the majority of the population while avoiding seasonal hurricanes?

Now, you can.

2.4.3 Visualization Features



Overview

The centerpiece is a satellite map focused on Southeast Asia, overlaid with geographic and demographic data. The application comprises of:

Interactivity & Navigation

- **Origin-Destination Tool** Locations to and fro are defined to simulate and analyze potential connectivity across the region.
- **Index Dashboard** Weights are assigned here to various indexes. The indexes include:
  - Tsunami Risk
  - Structural Durability
  - Environmental Impact
  - Operability
  - Population-Economic Importance

    - Final Feasibility Index

- **Map Scale** Simultaneously depict scales in kilometers and feet to interpret distances accurately.

- **Map Inset** Map highlighting the region of Southeast Asia, helping users unfamiliar with this region navigate the map.

- **Map Legend** Clarifies the symbology for key infrastructure types depict on the map.

- **City Labels** Major Southeast Asian cities like Jakarta, Singapore, Kuala Lumpur, and Ho Chi Minh City are marked for context.

- **Reset Button** Removes all calculations and resets all layer to default settings and brings users back to the center of the map.

Data Layers

Organized into categories, where ssers can toggle these layers on/off to tailor their view, comprising of:

- **Core Controls**
    - Pan, zoom, and perspective control.

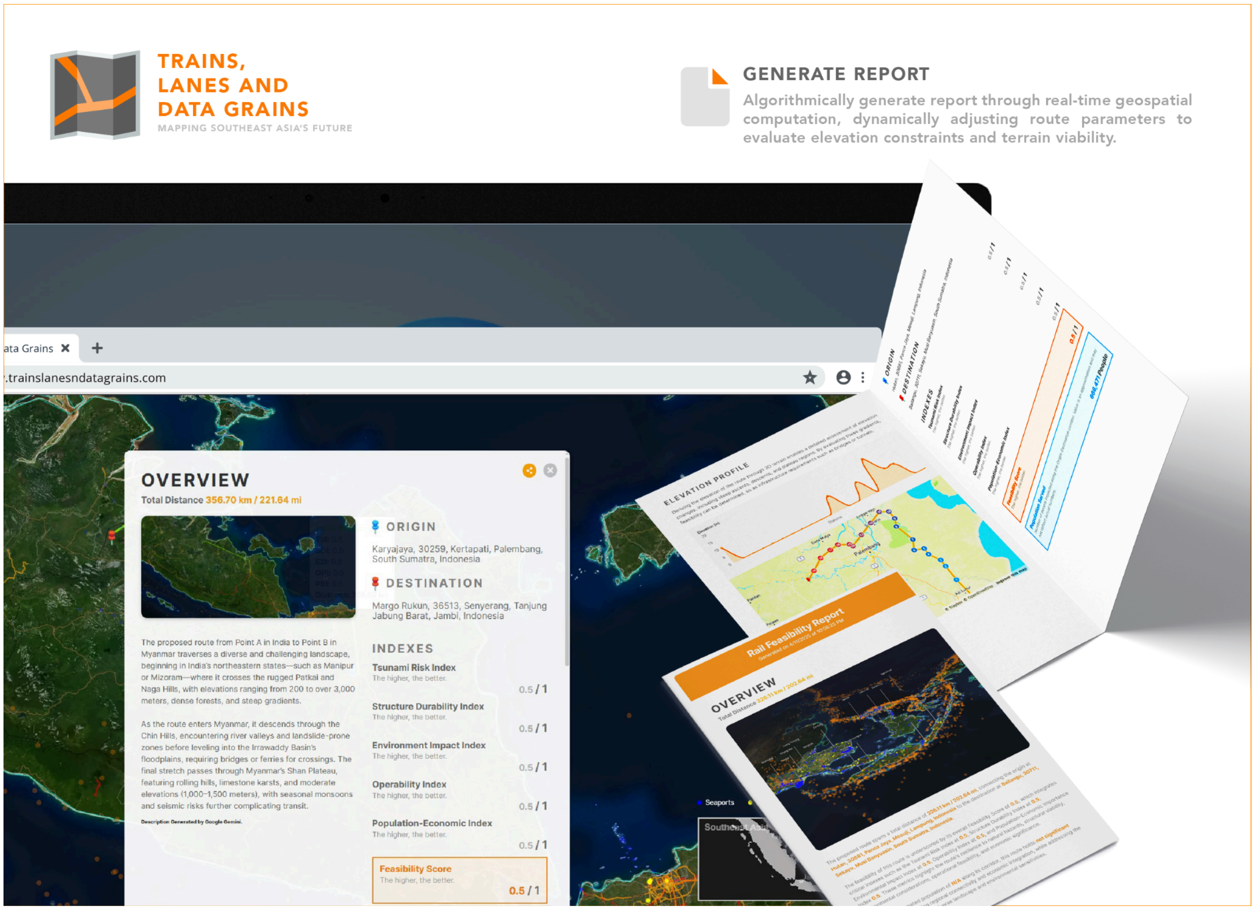
- **Climate Data**
    - Historical tsunami and earthquake counts
    - Humidity, forest coverage, and coastlines

- **Biodiversity Data**
    - Distributions of amphibians, birds, and mammals

- **Census Data**
    - Spatial population density
    - Spatial GDP per capita (PPP)

The interface spots a carefully considered typography and label placements, enhancing readability without overwhelming visual aesthetic, as balancing between detail and clarity allow users to interpret visualizations with ease. Granular data layers can be selectively activated—ranging from topographical features to infrastructural overlays—encouraging a more focused analysis. Real-time updates from the indexes' values trigger an instant recalibration of route, allowing immediate visualization of the impact of parametric changes.

2.4.4 PDF Export - Rail Feasibility Report



The follow fields are dynamically filled based on the contents calculated and displayed in the visualization, where each field will be marked as N/A if data is still loading or when it is not available.

OVERVIEW

Date Generated Timestamp Marks the time the report is generated.

Total Distance (km / mi) Shows the length of the route in both kilometers and miles

Route Thumbnail A snapshot is made to display the route and its geographical surroundings. Any layers toggled on will also be capture and reflect on this snapshot, helping to further illustrate how the route will overlap with population centers, points of interest, or other relevant data points.

Route Summary A report summary based on the indexes, which suggests the likelihood of this route helping to enhance regional connectivity and economic integration, with a sample description below:

“The proposed route spans a total distance of **326.11 km / 202.64 mi**, connecting the origin at **Hutan, 30681, Panca Jaya, Mesuji, Lampung, Indonesia** to the destination at **Bailangu, 30711, Sekayu, Musi Banyuasin, South Sumatra, Indonesia.**

The feasibility of this route is underscored by its overall **Feasibility Score** of **0.5**, which integrates critical indexes such as the **Tsunami Risk Index** at **0.5**, **Structure Durability Index** at **0.5**, **Environmental Impact Index** at **0.5**, **Operability Index** at **0.5**, and **Population-Economic Importance Index** at **0.5**. These metrics highlight the route's resilience to natural hazards, structural viability, environmental considerations, operational feasibility, and economic significance: This section explains the overall assessment of the project's viability.

Serving an estimated population of **567,942** along its corridor, this route holds **moderately significant** potential for enhancing regional connectivity and economic integration, while addressing the challenges posed by its diverse landscape and environmental sensitivities.”

Origin & Destination Specifies the starting point and ending point of the route.

INDEXES

All previously weighted metrics are integrated into the evaluation of the route . Each index contributes to the overall Feasibility Score, with values normalized on a 0–1 scale—where scores closer to 1 indicate more favorable outcomes.

Tsunami Risk Index Evaluates the route's susceptibility to tsunami.

Structure Durability Index Assesses the overall structural integrity within its environment.

Environmental Impact Index Evaluates the route's impact on biodiversity.

Operability Index Gauges how easily the railway can be maintained and operated while taking into account terrain and accessibility.

Population-Economic Index Evaluates the economic gravity with the goal of guiding development from areas with high levels of development to those with lower levels.

Final Feasibility Score A composite score, which is indicated as the summary in an orange box, illustrates the route's overall feasibility.

Population Served A demographic indicator, displayed in a blue box, shows the number of people the proposed route will cater to.

ELEVATION PROFILE

Elevation Chart with Map A line chart with markers, illustrating the changes in elevation along the route and their specific location

PATH COORDINATES

Markers Denoted by a serial number and a colour code to represents a specific point along the proposed route, with its corresponding latitude and longitude. These coordinates that plot the route, would be essential for remapping and surveying the route.

2.4.5 Usage Demonstration

The demonstration presented in this section are further illustrated in the video, accessible here. github.com/xuanx1/parsonsThesis-xuan/blob/main/04final/demo.mp4

Demonstration Transcript

Slide 1: *Trains, Lanes, and Data Grains: Mapping Southeast Asia's Future*
Southeast Asia is growing—fast. But how do we connect cities, villages—labour forces and economies across a region that's wildly diverse in geography, climate, and infrastructure? This speculative transport planning engine built on real data, and algorithms, reveals what's possible.

Slide 2: *The Tradition* The public sector and urban planners face immense challenges. Climate risk, environmental degradation, population surges. All while trying to deliver rail networks that are safe, cost-effective, and future-proof. Traditional planning just can't keep up.

Slide 3: *The Idea* This tool turns geographic and census data into a decision-making engine. Users can sketch rail lines across the map—and instantly assess their feasibility. It's like SimCity, but built for activists, planners, and anyone with a vision for better infrastructure.

Slide 4: *The Mechanism* Each line drawn is analyzed using five key indexes—**TSI**, the Tsunami Risk Index, **SDI**, the Structure Durability Index, **E2I**, the Environmental Impact Index, **OPI**, the Operability Index, **PEI**, the Population-Economic Importance Index. All of them combine to form a Final Feasibility Index—or **FFI**—scored from 0 to 1, 0 being highly unfeasible and 1 being very feasible.

Slide 5: *The Line* Let's say we sketch a route from Medan to Southern Sumatra, we can see a missing link here, which was a problem back in 2004 when a tsunami hit and authorities faced challenges in ensuring reliable evacuation and inflow of humanitarian aid.

Behind the scenes, the engine reads elevation data, calculate for tsunami risk, scans biodiversity zones, calculates population served—all to gauge the feasibility of such route.

Slide 6: The *Feedback* The charts break down the performance of the route drawn, and all the data is updated realtime on a dashboard—with a map snapshot, feasibility scores, and even, the coordinates of each station, with an option to export into a PDF report.

Slide 7: The *Audience* City planners. Environmentalists. Engineers. Curious citizens. Even bored bureaucrats. Whether you're designing real infrastructure or just dreaming of better cities—this tool gives you the power to explore the future, without the bulldozers.

Slide 8: *The Next Frontier* The tool is built to grow. Add more datasets. Plug in real-time APIs. Layer in social, cultural aspect. And someday, train AI agents to generate proposals based on policy goals or community needs.

Slide 9: *The Vision* The future of rail infrastructure isn't just concrete and steel. It's data. Imagination. And tools that let *everyone* be part of the planning conversation. Southeast Asia deserves smart, resilient, people-powered design.

Slide 10: *The Action* So Where would you build? Where would you connect? The map is waiting. Draw the line. Test your theory. Reimagine what's possible—one pixel, one route, one dataset at a time.

3. Results and Findings

3.1 Datasets

Climate Data Historical Tsunami, Earthquake Counts, Humidity, Forest Coverage, and Coastlines

- **Temporal Inconsistency** Many datasets varied in their update frequency. For instance, earthquake data was regularly updated, while forest coverage are only updated every few decades. Humidity data relied on seasonal averages from historical datasets.
- **Spatial Resolution Mismatch** The sources provided data at differing spatial resolutions. Raster datasets, particularly those in GeoTIFF format (e.g., humidity and forest cover), required alignment in QGIS to ensure uniform 100m x 100m grid cells across all layers.
- **Format Conversions** Considerable computational power is required to convert GeoTIFF (used for raster-based calculations) to GeoJSON (used for classification and scoring). Conversion is also required to normalize of cell values, which includes inversion, in cases where high values indicated negative impact.
- **File Size Constraints** To meet the web deployment requirements, files hosted must be below < 100MB. Large raster datasets were clipped, resampled, or processed into vector tiles where appropriate or hosted on Mapbox as maptiles as the last resort.

Biodiversity Data Spatial Distribution of Amphibians, Birds, and Mammals

- **Format Standardization** Because many of these layers are originally raster-based files, they are vectorized to ensure compatibility with other layers and ease of parsing data within each cell.

Census Data Spatial Distribution of Population and GDP Per Capita (PPP)

- **Population Density** This dataset had the highest spatial resolution among all layers, at 30m, causing its size to exceed cloud storage limits. To address this, the GeoTIFFs are hosted on Mapbox and dynamically queried and fetched during runtime.

- **GDP Per Capita, PPP** This layer had the poorest spatial resolution among all layer, as most of such data are often aggregated at a regional or national level. To compensate for it, proxies such as urban proximity, transport network density, and forest coverage were integrated into calculations to approximate economic activity.

3.2 Process

Preloading vs. Realtime API Calls

Two distinct strategies were considered:

- **Preloading and Precomputing** All indexes were precomputed for every single 1km by 1km cell that is possible to be fitted into the boundaries of Southeast Asia and stored as a single GeoJSON. This reduced runtime processing but will lead to inaccuracies as newer datasets became available.
- **Realtime API Calls and Index Calculation** This approach will improve calculation accuracy, since the most updated data will be fetched. While this technique is more resource-intensive, it enabled responsive recalculations based on user-defined parameters.

Eventually, a hybrid approach was adopted—preloading base data for data that are more routine and predictable, such as humidity and popu;ation distribution while enabling real-time calculations on datasets that are more time sensitive like earthquake data.

3.3 Optimizations

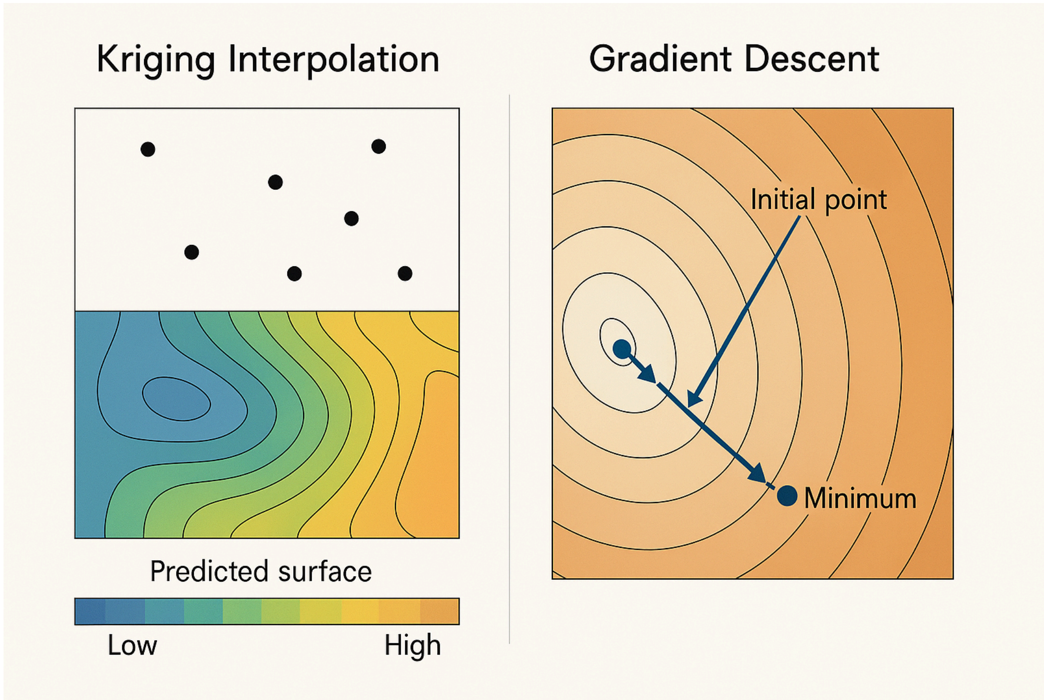


Figure: Comparison of Kriging Interpolation and Gradient Descent

Left: Kriging creates a continuous surface derived from points in close proximity, calculating values across unsampled areas to create a seamless surface.

Right: Gradient Descent charts a path from an initial point toward a "better" spot by following the path with the least "cost" within a space.

Kriging A spatial interpolation technique used to estimate unknown values based on the spatial correlation of known data points. In this project, Kriging was applied mainly to environmental data that had uneven sampling or low-resolution input. This fills in data gaps to maintain continuity in index calculations and reduce spatial discontinuities and avoid biasing route optimization toward areas with simply better data coverage.

"Path of Least Cost" Gradient Descent An optimization algorithm adapted to optimize railway corridors by minimizing environmental costs and maximizing economic benefits — essentially maximizing the **Final Feasibility Index** over the allocated space.

1. **Initialization** The algorithm starts with a naïve path — a straight line between the origin and destination plotted by the user.

2. **Evaluation** The algorithm finds and plots the intermediate points on pre-calculated grids with the value of the Feasibility Score (and other indexes specified in the settings), aggregating the environmental and socioeconomic indexes along the proposed line within the land boundaries encapsulating these 2 points.

3. **Perturbation** Adjustments are made to the path geometry, shifting segments toward neighboring cells with better composite scores. These perturbations are guided by the "gradient" of the feasibility scores grid— in other words, the direction in which scores improve.

4. **Iteration** This process repeats iteratively, each time moving the path slightly in the direction of a Final Feasibility Score closer to the settings.

5. **Convergence** The process stops once improvements fall within the value of the indexes specified in the settings. A bezier curve function is applied to smoothen the curvature.

4. Conclusion

4.1 Benefits to Southeast Asia

A meticulously planned regional transport network is foundational to economic integration in Southeast Asia. By improving the mobility of goods, services, and human capital, such infrastructure accelerates trade and regional economic growth. Efficient connectivity fosters cross-border collaboration and strengthens the competitiveness of emerging economies within and beyond ASEAN (Asian Development Bank 2019).

This tool also promotes economic and development equality by linking rural and urban zones. In regions where economic opportunities are often concentrated in large metropolitan centers, connecting outlying communities helps reduce such inequalities and extends access to jobs, healthcare, and education to them (World Bank 2020) through improved accessibility, leading to a more inclusive development.

Designed with regional climate in mind, the infrastructure accounts for the wide array of challenges unique to Southeast Asia, such as monsoons, high humidity, and tsunami risks. This reduces the long-term cost of maintenance and increases the durability of infrastructure investments (UNESCAP 2021).

The platform encourages sustainable development by minimizing land disturbance by integrating with existing infrastructure and avoiding ecologically sensitive zones. This aligns with global calls for low-impact transportation solutions and the reduction in greenhouse gas emissions from new construction projects (Intergovernmental Panel on Climate Change 2022).

More importantly, the project delivers policy-relevant insights for urban planners and government officials. Its evidence-based framework supports data-driven decision-making and long-term planning, especially as Southeast Asian countries seek to balance rapid urbanization with sustainability targets (ASEAN Secretariat 2021).

The tool introduces a novel layer of public participation and transparency into a traditionally top-down infrastructure development process. This empowers researchers, and activists to simulate routes, propose alternatives, while assessing social or environmental impacts, opening space for a dialogue and eventually, a more equitable development (Transparency International 2023).

Finally, disaster-aware design is embedded at its core. This is key as Southeast Asia is acutely vulnerable to climate-related hazards such as sea-level rise, tsunamis, and earthquakes. Since the tool actively avoids routing railway lines through high-risk zones, it guides the state's investments toward safer and strategically located urban clusters, thereby protecting vulnerable communities and enhancing long-term commitment towards developing last inter-regional connectivity (Global Facility for Disaster Reduction and Recovery 2022).

4.2 Disadvantages of Technique to Southeast Asia

While such tools offer a huge potential for inclusive and data-driven planning, their effectiveness is constrained by several key challenges—many of which are especially acute in the Southeast Asian context.

First and foremost, data quality and its availability remains as huge obstacles. Much of the region lacks comprehensive, current, and openly accessible data. In countries where the practice of Open Data is still developing, datasets may be incomplete or outdated, leading to blind spots in analysis and the risk of misguided infrastructure decisions—especially in underserved or border regions (Open Data Watch 2022;

World Bank 2021). **The tool's outputs are only as reliable as the datasets it consumes.**

Another related concern is the over-reliance on quantitative data. While numbers can model terrain, derive population density and economic importance, they are usually unable to capture qualitative factors like cultural, religious and historical. Hence, places may be overlooked simply because they lack formal spatial encoding (UN-Habitat 2020).

Scalability issues will potentially occur when applying the tool to unfamiliar geographies or less-documented areas, impairing its functionality and reduce the accuracy of its recommendations (González et al. 2021).

Moreover, the tool carries a risk of oversimplifying current realities as it currently does not consider qualitative issues like land acquitsition and local opposition to the central goverment's intervention (Asia Indigenous Peoples Pact 2022). Thus, the tool should complement and not replace studies regarding community participation and ethnographic research in its planning.

In addition, inequality in technology access and literacy could unintentionally exclude those who are most in need of participatory tools. Despite the calculator's accessible design, it still requires stable internet connection and basic geographic knowledge to function well. In regions where such infrastructure is limited, and english is not the primary language, the tool, might ironically reinforce existing divides (UNESCAP 2022).

Lastly, there is the potential of policymakers or urban planners abusing this tool, as its objectivity will causes these parties to view its results as definitive decisions rather than well-informed recommendations. This causes overprioritization and fast-tracking on a project spanning numerous disciplines without enough analysis and feasibility studies conducted. Therefore, it is essential to present the tool as a starting point for an open dialogue, and not a final verdict (Transparency International, 2023).

4.3 Further Areas of Interest / Consideration

This planning tool will become even more relevant when political and social boundaries are taken into account. Because Southeast Asia is home to a diverse ethnic groups where their reside in their autonomous regions, usually away from the central government's intervention. With such culturally sensitive areas, along with this kind of decentralised governance, planning infrastructure without taking these into account may exacerbate tensions uneccessarily. Therefore, incorporating culturally significant areas into the list of consideration is key in fostering inclusive development (ADB 2020; IWGIA 2023).

In additon, the application of reinforcement learning (RL) can propose auxiliary or phase transport networks that preserve continuity and coherence over time by implementing a learning algorithm that adjusts based on past results. This approach allows planners to maintain consistency while building on existing infrastructure in areas with uncertain funding (Silver et al. 2016; Gama et al. 2022).

The tool's modularity enables expansion to other infrastructure types instead of just rail infrastructure. Similar analyses can be applied to optic fiber networks, energy corridors, highways, and even pedestrian infrastructure. This way, the engine can be transformed into a multi-faceted planning tool through the modification of the weights of the constituting indexes, which will make it useful to other agencies in addition to transport ministries (UNOPS 2021; World Bank 2022).

Real-time data integration can also be considered as dynamic datasets such as weather reports, traffic congestion, or status updates would greatly improve the tool's accuracy and responsiveness. As urban volatility and climate risks increase, it is important to incorporate temporal awareness, extending beyond long-term planning and enables applications such as ongoing maintenance scheduling and simulating real-time disaster response (OECD 2021).

Introducing community-driven data, which include information that is missing from official datasets, such as maps of unofficial housing, protest zones, or places of cultural significance, can give communities that have traditionally been left out of development decisions, the visibility and enabling institutions, or local governments to promote bottom-up planning instead of the usual top-down approach (Map Kibera Trust 2022; UN-Habitat 2021).

Finally, if climate goals and public policies are integrated, the tool can evolve into a platform that aids government decision-making, measuring how well the choices are in line with international frameworks and UN's Sustainable Development Goals (SDGs). Trade-offs can be visualised by modelling various scenarios against these indicators. (UNEP 2023; World Bank 2023).

4.4 Final Statement

This project demonstrates that the concept of combinatorial optimization can be an effective tool in planning public transport networks and promote regional connectivity in Southeast Asia, particularly in the face of the region's challenging terrain and unpredictable climate. By integrating indexes and key indicators, the tool provides a data-driven approach to rail line and station placement. The proposed rail network gives space for the general public to conceptualise hypothetic connections that has yet to exist but should have existed.

The project began with a deceptively simple question: Where should the next railway go? But beneath that question lies a complex network of environmental, social, and economic realities to be considered—many of which are invisible in conventional transport planning tools. Trains, Lanes, and Data Grains aims to bring those realities to the surface through a visual, data-driven interface that empowers users to draw, test, and imagine infrastructure in new ways.

What emerged is more than just a feasibility calculator. It's a speculative engine—a way of exploring possibility, weighing risk, and surfacing tradeoffs in regions undergoing rapid transformation. Through the use of open-source tools, publicly available datasets, and geospatial logic, the platform demonstrates how accessible, interpretable, and actionable urban planning can become when reimagined through the lens of interaction and participation.

The ability to calculate five distinct indexes—Tsunami Risk, Structural Durability, Environmental Impact, Operability, and Population-Economic Importance—adds multidimensionality to a simple act: drawing a line on a map. After this, that line is no longer abstract. It becomes accountable. It carries with it implications of safety, cost, impact, and opportunity. In that sense, the tool transforms every user—from students to policymakers to activists—into a planner, equipped not with raw speculation, but with spatial insight.

As Southeast Asia continues to grow and continue to urbanize, tools like this will become increasingly important—not to dictate solutions, but to highlight possibilities. In addition to being comprehensive and substantiate, the future of infrastructure should also be influenced by the people who will use it. This calculator, while simple, plants a seed in that direction. A seed of open data, transparent metrics, and visual imagination.

The code is written. The map is drawn. The lines are waiting to be tested, challenged, and redrawn. The future of rail—and the future of urban planning itself—is one click, one shared vision and numerous discussion away.

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