IIEP Technical Note

Multi-criteria decision analysis for site classification: Assessing natural hazard risks for planning the location of educational facilities

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INTRODUCTION

Every education system is mediated, shaped, and constrained by its environment. Elements of physical accessibility for students and teachers, the slope of the plot of land a school building is constructed on, the natural hazards present in the area, and the measures taken to counter them are all factors that play a role in the way citizens interact with the education system and which can influence the demand and supply of education within a country.

The challenge of providing quality education to all children and youth in every country is enormous, particularly where context-appropriate learning environments and schools are scarce (Bonner et al., 2011). An illustration of this is an estimation made by the World Bank in 2009 (Theunynck, 2011) of construction needs from 2009 to 2015, which for sub-Saharan Africa amounted to 2 million new classrooms, along with associated facilities (e.g. water, sanitation and hygiene [WASH]). Likewise, according to UNICEF, 'providing universal pre-primary, primary and lower secondary education in low-income and lower-middle-income countries by 2030 will cost an estimated US$340 billion a year' (Watkins, 2016).

School construction is the most expensive item of all capital investments for ministries of education around the world (Gershberg, 2014). As such, there is a great need to factor the environmental conditions of the area where schools are or will be built into the design of school infrastructure (e.g. stilts for schools in flood-prone areas, earthquake-resistant schools in areas with strong earthquakes). Having knowledge of these environmental conditions, particularly those that are locally relevant, is of paramount importance, as it will determine the cost-effectiveness of investments. This is becoming more pressing than ever with the acceleration of the climate catastrophe and the need for governments to account for strong climate-related disruptions to the education system.

The choice of where to build new schools is influenced not only by environmental issues but also by social, political, and economic ones. Therefore, these factors also need to be considered in the decision-making process. Choices concerning school location are affected by the local context and hence should be tailored to national, regional, and local conditions. Traditional micro-planning and school-mapping techniques (Caillods et al., 1983; Hallak, 1977) take into account some of these factors but are usually limited to including data on the location of existing schools and on the distribution of the population in the territory. As such, most of these confounding variables are ignored, particularly those related to the environment. The twofold methodology outlined in this technical note aims to fill this gap, by using a variety of data sources and methods to account for multiple factors and thus attain a richer perspective than is possible from using conventional methods.

This technical note proposes a two-part geospatial methodology for assessing risks related to natural hazards and the interaction between these and other factors (including local norms and laws on education), in order to better plan the location of schools using *multi-criteria decision analysis* (MCDA) techniques. *Part 1* describes a *geospatial risk assessment methodology* for educational facilities. This approach is flexible and allows planners and education ministries to select the prevailing natural hazards in their local context. The risk information is presented geospatially in terms of a numeric risk index using a risk assessment formula.

Part 2 proposes the use of an MCDA technique to inform policy decisions in educational planning. In particular, a site suitability analysis is performed; this can be easily tailored to different needs and contexts. As the model is customizable, educational planners can attribute various levels of importance to criteria such as existing hazards, terrain, land cover, and connectivity when analysing potential areas for constructing new educational facilities or for the relocation of existing at-risk facilities. This analysis also produces suitability risk maps, which can be shared and used as a decision-making support and communication tool. This helps to ensure that new schools will be built in low-hazard-risk zones or built with the relevant specifications, also taking into consideration optimal connectivity to the road network and waterways to make educational facilities more resilient to disasters. This MCDA technique uses the output of *Part 1* as one of its inputs, integrating the results from the natural risk assessment into the suitability calculations for a particular area or territory.

So that users of this methodology can apply, replicate, or customize it, the approach is demonstrated here using free, open-source data and software, and information on data sources is provided. Where official government information may be unavailable, guidance is given on how to find relevant information online. This technical note also includes step-by-step instructions for geospatial techniques, including graphical models and background knowledge for both *Part 1* and *Part 2*.

The code and all supporting documentation for both parts of the methodology are available via this hyperlink, which also contains a QGIS plugin with the same functionalities. There is also a Zotero library containing all the references cited in this technical note.

1. GEOSPATIAL RISK ASSESSMENT

Part 1 details the various steps in the process for carrying out a geospatial hazard risk assessment, illustrated by an analysis for Aceh Province in Indonesia. This assessment will shed light on which areas have elevated hazard risks and which schools are located in those areas. It demonstrates that an informed use of open-source geospatial data can produce meaningful outputs to inform decision-makers and planners who are considering hazard risks.

Geospatial risk assessments and risk indices are widely used across many fields to measure and compare risks for different geographical areas. Among the many different approaches to and types of risk assessment in use worldwide are the World Bank's Climate and Disaster Risk Screening Tools (World Bank, 2022), the OECD's States of Fragility Index (OECD, 2022), and The Economist's Global Food Security Index (The Economist, 2022). Another such assessment, produced at the global level, is the INFORM Risk Index (see DRMKC, 2021a). This index has been used as an aid in humanitarian crises and disasters by providing country-level risk scores across multiple categories to support decision-making, prevention, preparedness, and response (DRMKC, 2021a). A further assessment is the World Risk Report, which uses an index-based measurement to display degrees of disaster risk associated with extreme natural events; it is available for 181 countries and calculated on a country-by-country basis (IFHV and Bündnis Entwicklung Hilft, 2020).

At the country and regional levels, research has demonstrated that risk assessments can aid in emergency and disaster response. Examples of disaster risk management include: a flood risk assessment for Myanmar with hazard and exposure indexes, using statistical indicators, geospatial data, and earth observations (Phongsapan et al., 2019); and the Marsh McLennan Flood Risk Index (Marsh McLennan, 2022), which is calculated using temperature rise predictions to model potential flood risk at the national level for all countries in the world.

1.1. CONCEPTUAL APPROACH

Many risk indexes are used to measure risk for various elements, with different levels of disaggregation. While risks may be calculated in a variety of ways, a simple and very common method is with the following formula:

$$\text{Risk} = \frac{(\text{Hazard} \times \text{Exposure} \times \text{Vulnerability})}{\text{Capacity}}$$

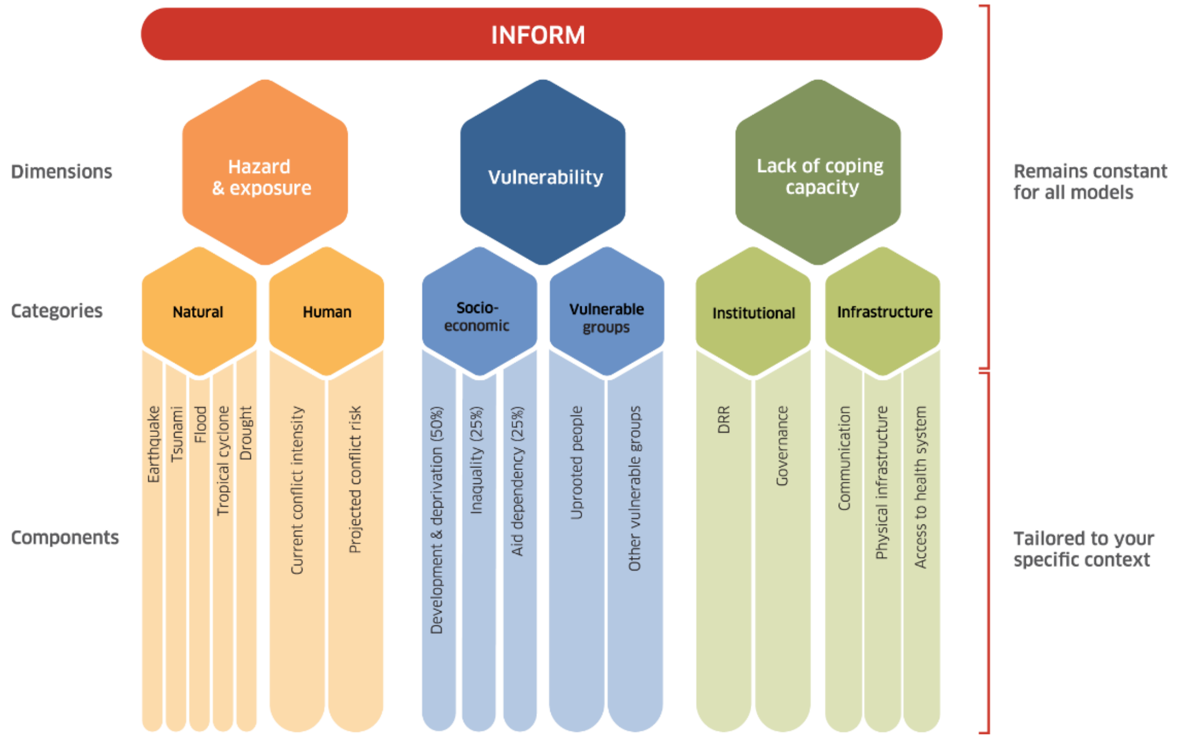
Note that the numerator contains factors that can drive risk up as they increase (e.g. greater vulnerability, all other things remaining equal, will increase the risk profile), while the denominator reduces risk as it increases (i.e. even when there is a high level of hazard, exposure, or vulnerability, a high level of capacity mitigates the risk). However, capacity is very much linked to vulnerability, so in some risk formulas the denominator is not present, as is the case with the INFORM Risk Index. In some conceptual approaches, hazard, exposure, and vulnerability are replaced by severity and likelihood, with the same result.

When calculating the risk index for the example presented in this document, the approach of the United Nations Office for Disaster Risk Reduction (UNDRR) and the INFORM Risk Index developed by the Disaster Risk Management Knowledge Centre (DRMKC) of the European Commission (DRMKC, 2021a) was followed. The INFORM Risk Index differs from the UNDRR and other literature slightly, as it splits the variables into only three dimensions, merging Hazard and Exposure, keeping Vulnerability, and using the inverse of Capacity (i.e. Lack of coping capacity) as a numerator instead of Capacity as the denominator. The formula is:

$$\text{Risk} = (\text{Hazard \& Exposure})^{\frac{1}{3}} \times \text{Vulnerability}^{\frac{1}{3}} \times \text{Lack of coping capacity}^{\frac{1}{3}}$$

The INFORM formula is a multiplicative one (with each factor compounding the others) such that the resulting risk index is a geometric average of its components, hence the exponents 1/3. The INFORM Risk Index is demonstrated with the sub-categories and components in *Figure 1*.

Figure 1. INFORM Risk Index methodology



Source: DRMKC (2021a).

The risk values are calculated using an index-based method, with all indicators ranked on a scale of 0–1 or 0–10 (where 0 indicates the lowest and 1 or 10 the highest risk). These indicators are then combined using a weighted geometric average to form an overall risk index. The data produced from the INFORM Risk Index are usually calculated at the national scale, but the calculations can also be done at different levels, such as regional or sub-regional scale, to arrive at estimates of risk at the local level.

The methodology presented here does not need to include all the categories or indicators used by the INFORM Risk Index; rather, these should be thought of as guides to be customized to each situation. Depending on data availability and expert knowledge, components can be changed and various categories of risk calculated. Furthermore, the methodology allows the user to determine the weight to assign to each of the risks, so that their relative importance can be factored into the compound hazard index. This will help inform educational planners about the risk level for education facilities and paint a picture of where hazards are most likely to impact education continuity. However, planners must correlate the calculated hazard index with the 'ground truth' (which, though ideally measurable, frequently remains anecdotal) of how the education system and individual education facilities are impacted. It must be stressed that in actual practice, data quality and availability, expert knowledge, general discussions with local stakeholders, and other factors all play important roles in selecting the final features to include in the model.

Note that while the generic form of the risk formula includes measures of vulnerability and capacity (or lack of coping capacity, as in the case of the INFORM Risk Index), the model developed in this note includes only the elements of hazard and exposure. While this may seem restrictive, the model allows users to combine its outputs with their own calculations for the two missing elements. Since information on hazard and exposure is more easily generalizable, and the data sources easier to access for any country, a decision was made not to expand this model to include measures of vulnerability and capacity, as it would then be too restrictive in some scenarios or the data requirements would be too onerous for some countries. Furthermore, obtaining granular, localized data for vulnerability and capacity can be challenging, whereas data on natural hazards can be obtained from national sources (e.g. national meteorological agencies) or earth observations (e.g. using Google Earth Engine). *Table 1* presents, for each risk category, possible variables that can be used for a more in-depth analysis.

Table 1. Potential components and their data sources

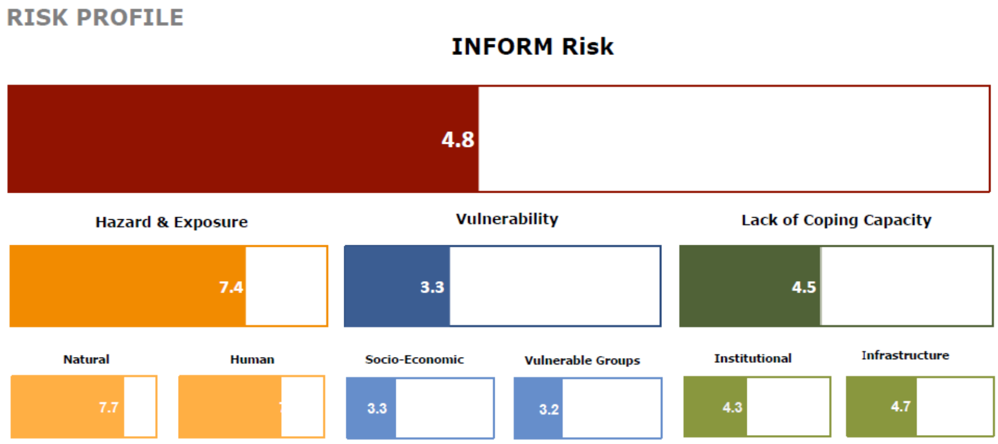
Dimension	Potential components	Potential data sources
Hazard & Exposure	Earthquakes	National meteorological agencies or earth observation platforms
	Tsunamis	
	Floods	
	Severe weather	
	Landslides	
	Volcanos	
	Drought	
	Pollution	
	Famine	National statistical agency or World Food Programme
	Conflict intensity	Ministry of Defence or Armed Conflict Location & Event Data Project (ACLED)
	Prevalence of landmines and other unexploded ordnance	Ministry of Defence
Vulnerability (local level)	Materials of the floors in schools	Ministry of Education
	Materials of the roofs in schools	
	State of the infrastructure of the schools	
	Schools built on stilts	
	Schools built using earthquake-resistant techniques and materials	
Capacity (school level)	Existence of contingency plans	
	Existence of disaster risk reduction mechanisms	
	Existence of emergency funding	

Source: Authors.

In the example presented in this document, the hazard and exposure risk will be calculated for natural hazard events in Indonesia at the provincial scale using a customized index including earthquakes, tsunamis, floods, severe weather, landslides, and volcanos.

The Indonesian Risk Profile from INFORM (DRMKC, 2021b) shows that Indonesia has an overall risk score of 4.8, with hazard and exposure being the highest-risk category, having a risk score of 7.4. Of the components considered, natural hazards have a particularly high risk score, 7.7, as seen in *Figure 2*. The most frequently occurring natural hazards identified for Indonesia were earthquakes, tsunamis, and floods. These statistics help to inform the risk analysis by identifying the hazards of most concern for the country. Consultation with national experts, ministry officials, and other knowledgeable stakeholders can help to select which variables to include within each dimension. Once hazards have been mapped at the local level, geospatial data on education facilities can be used to triangulate this information and subsequently identify those facilities that are most at risk of being impacted by hazards. Such information should be customized according to the administrative region or ministry of education leading the study, as some hazards are more relevant in specific locations than in others.

Figure 2. INFORM Risk Profile for Indonesia, 2021



Source: DRMKC (2021b). Additional hazard datasets. *Note*: Discrepancy in average (in red) is due to rounding.

Additional hazard datasets that can be used if country-level data and portals are not available include the Global Assessment Report (GAR) from the UNDRR, which has developed and published many different global and regional datasets of disaster-related data. The GAR15 Global Exposure Dataset was compiled globally by combining statistical information (such as social, economic, building, and capital stock data) to produce a top-down exposure index, represented in raster grids of 5 km × 5 km or 1 km × 1 km.

Many open-source disaster- and hazard-related datasets can also be accessed. Listed in *Table 2* are some key global data sources from which hazard data can be extracted. Note that regional or national datasets are not listed, although they should be the first places to look when creating an index for a specific country.

Table 2. Data sources for natural hazard data

Name	Data type	Hyperlink	Source
GAR Risk Atlas Dataset	Global hazards	Data download Data portal	GAR, UNDRR
Natural Hazard Viewer	Global hazards	Data download Data portal	National Oceanic and Atmospheric Administration (NOAA)
Aqueduct Floods	Flood hazards (global scale)	Data portal	World Resources Institute (WRI)
Aqueduct Water Risk	Water hazards (global scale)	Data portal	WRI
Pacific Risk Information System	Pacific region hazards	https://risk.spc.int/	Joint initiative

Source: Authors' research.

Additional social or human hazard data may also be included. For example, two common data portals that host data on conflict hazards or displacement numbers are presented in *Table 3*.

Table 3. Data sources for additional hazard data

Name	Data type	URL	Source
Uppsala Conflict Datasets	Multiple conflict datasets (global scale)	Data download	Uppsala Conflict Data Program (UCDP)
Global Internal Displacement Database	Displacement figures per country (global scale)	Data portal	Internal Displacement Monitoring Centre (IDMC)

Source: Authors' own research.

1.2. DATA REQUIREMENTS

This section looks at the geospatial data that are necessary for educational planners to be able to plan risk-mitigation measures for educational facilities. When undertaking geospatial analyses, it is important to know what data are required, which are available, and where these can be found. It is also important to understand the capability and reliability of the data, especially if they are obtained from open sources. Reliable sources of data include periodically collected administrative data and data collected sporadically by governments or other organizations. Both types are usually available from government websites, national information systems, and other reliable open-source data websites.

Box. Country and regional boundaries and general datasets

Country and regional boundaries are at the heart of the methodology, as they circumscribe the analysis and act as a defining force behind potential policies to be implemented based on the analysis results (i.e. factors such as the extent, geographical features, or political configuration embedded in these boundaries can determine whether a particular policy is better than another). They are also sensitive data, since they are implicitly political statements declaring ownership over land and rule over its people. As such, the use of official boundaries is essential, as having the correct administrative information will facilitate smoother instrumentalization of the results.

Apart from country and regional boundaries, several datasets that pertain to education and risk mitigation are fundamental for the correct implementation of this methodology. These datasets will vary depending on the national or regional context, particularly those relating to natural hazards, while others, such as road networks or elevation, are mostly universal.

When downloading country borders or other general datasets, it is important to be clear about where the data come from. Where possible, it is better to use datasets from official government sources to ensure that the data are correct and reliable for each country context. Efforts should be made to use official data whenever possible and to contribute to the creation, maintenance, and dissemination of government-produced data.

If such data cannot be found on government websites, other sources may provide this information. The official source for internationally compatible boundaries is the UN Second Administrative Level Boundaries (UN SALB) Programme.

Another source is the Humanitarian Data Exchange (HDX) developed by the UN Office for the Coordination of Humanitarian Affairs (OCHA), which is a platform for accessing multiple types of administrative datasets. HDX has a range of data, including data from OpenStreetMap (OSM).[1] Note that this should only be used as a last resort, and that adequate disclaimers should be put in place to inform readers or users of the non-official nature of these boundaries. These data come from a variety of sources, including governments and UN agencies. It is important to check the source and metadata to understand the limitations of the data; for example, data from OCHA may not be officially validated by the national government. Some data may be available for the whole country, while other data may be available only per state, province, region, or city.

[1] Data from OSM can also be directly downloaded into QGIS using a plugin, such as the 'QuickOSM' tool, which allows the user to import and download different OSM data for a designated region.

For the example presented in this note, general data for the study area in Aceh Province in Sumatra, Indonesia, were downloaded (see *Table 4*). These data contain the official administrative boundaries which delimit the extent of the analysis, as well as roads and waterways layers which are used as inputs for the MCDA in *Part 2*.

Table 4. Data sources for general data and administrative boundaries

Name	Geospatial layer type	File downloaded for example	Source
General administrative boundaries	Vector – Polygon Shapefile (SHP)	Indonesia – Subnational Administrative Boundaries	HDX, Badan Pusat Statistik (BPS – Statistics Indonesia)
Waterways	Vector – Polygon or Line Shapefile (SHP)	Humanitarian OpenStreetMap Team (HOT) Indonesia (Sumatra) Waterways (OSM Export)	HDX, OSM
Roads	Vector – Polygon or Line Shapefile (SHP)	HOTOSM Indonesia (Sumatra) Roads (OSM Export)	HDX, OSM

Source: Authors.

1.2.1. Hazard data

Geospatial data on hazard and disaster risk are readily available at the global scale, and some country-level datasets are also available.

For the example in this paper, regional hazard data from the Indonesian InaRISK data portal were used. InaRISK is an assessment portal that uses a private ArcGIS server to host data on disaster hazards, risks, and vulnerabilities for Indonesia. This portal was created via a joint initiative between the Indonesian government and multiple UN agencies and international organizations, including UNDP and UNESCO (BNPB, 2021). The aim of the portal is to disseminate disaster risk information to local and regional governments for better disaster risk reduction planning and programme implementation.

Based on the InaRISK portal, the Indonesian National Agency for Disaster Countermeasure (BNPB) has created their own risk index, the Indonesian Disaster Risk Index. This index focuses on natural hazards, rather than on overall risk (by excluding other risks such as violence, conflict, and insecurity), and considers natural phenomena that are prevalent in the region, such as earthquakes, floods, and volcanic eruptions. Vulnerability is calculated based on socio-cultural, economic, physical, and environmental factors. Capacity is assessed using regional resilience based on a number of priorities, including policies and institutions; risk assessment and planning; training and capacity building; and disaster preparedness, prevention, mitigation, and recovery (BNPB, 2018). The index uses the following formula to calculate risk:

$$\text{Risk} = \text{Hazard} \times \frac{\text{Vulnerability}}{\text{Capacity}}$$

For the example, the individual hazard data layers exported from the InaRISK portal were used to create a custom risk index, rather than using the precalculated risk index just described. The methodology allows the user to customize their risk index to the study context, taking into account data differences, as different countries may not have the same hazard data available, risk relevance may vary between countries and regions, and the relative weights given to different risks depend on the specific context.

1.2.2. Exposure data

Generally speaking, exposure refers to the assets or people that are exposed to a certain hazard. In other words, exposure data consist of the elements that are susceptible to the hazard risk and which will be analysed in the light of their relative location with respect to the hazards. These could be the points or polygon locations of infrastructure, such as education facilities, hospitals, or houses, and effectively act as the units of the risk measurement. They are usually baseline or general data and can be found on country websites and data portals or on open-source websites such as those of OSM and HDX.

In the Indonesia example, for the purpose of using the data for micro-planning purposes, the school locations were used to measure the exposure of education facilities to risks. These data on education facilities were obtained from the HDX website.[2] The layer has multiple fields, which contain information on each school: province, district, sub-district, village, address, school level (e.g. elementary, junior, vocational, and senior high school), and school name. It is also important to check the metadata to note the data source and year. For this data layer, the source is UN OCHA and the Indonesian Ministry of Education, and the year is 2015.

1.2.3. Vulnerability data

Vulnerability data may be obtained from the qualitative analysis of a structure, for example by examining a school building's construction material, damage, or scheduled maintenance. These factors will affect the capability of the structure to withstand a disaster event. Vulnerability data may not be easily accessible for all locations and may need to be digitized or collected based on example area and site analysis. Alternatively, some countries or authorities may have this information readily available in their education monitoring and information systems (EMIS), gathered through yearly school censuses. Vulnerability data were not included in the geographic models created in the Indonesia example. However, the results from this example will aid in decision-making regarding the collection of vulnerability data, as the output of the models in the example can provide valuable information on risk-prone areas and education facilities. For instance, the results from this example can highlight at-risk regions or local areas and facilities where additional vulnerability field data would need to be collected. Examples of variables that can be used for assessing vulnerability data are presented in *Figure 1*. Note that while school-level vulnerabilities are of particular interest for this methodology, the use of community, household, and local vulnerability indicators can help to enrich the analysis and reflect the conditions around schools more accurately.

If collection of vulnerability data is required, a method for data collection through mobile applications, such as UN-ASIGN, is recommended.[3] Mobile applications for collecting field data allow schools and people on the ground to collect accurate, reliable vulnerability data and transmit them back to the geographic information system (GIS) team for further analysis.

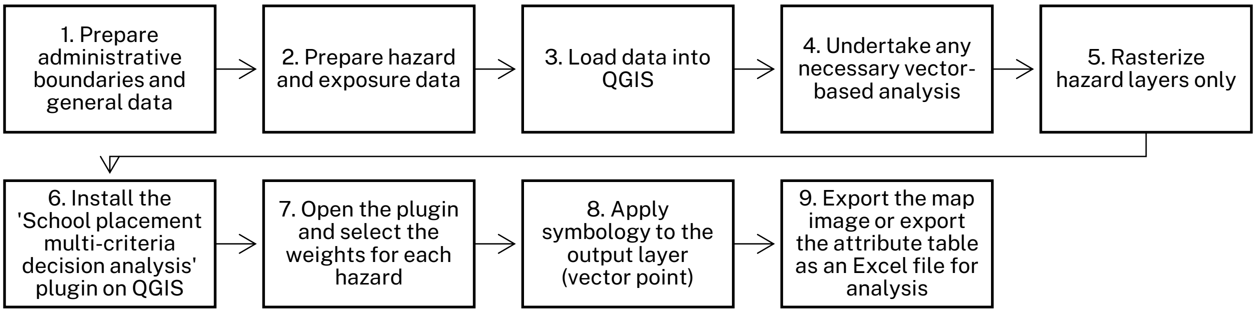
1.3. METHODOLOGY

The geospatial risk assessment will be calculated in QGIS by following the procedure outlined in *Figure 3*. This sets out a simple and customizable assessment method which can be used to calculate the exposure risk of facilities. The rest of this section is numbered according to the steps shown in *Figure 3*.

[2] This was done to show the mechanics of the methodology and does not constitute an endorsement of the particular dataset. At all times nationally approved databases must be used.

[3] UN-ASIGN is a free application offered by UNOSAT (the United Nations Satellite Centre) and AnsuR Technologies to assist the humanitarian and wider development community in the collection of photos, assessments, and geolocated text messaging in the field. The app is specifically designed to work over no- or low-bandwidth connections, allowing convenient surveying in remote areas. The geotagged photos are then displayed on UNOSAT's LIVE map along with other crowdsourced images.

Figure 3. Methodological outline for *Part 1*



Source: Authors.

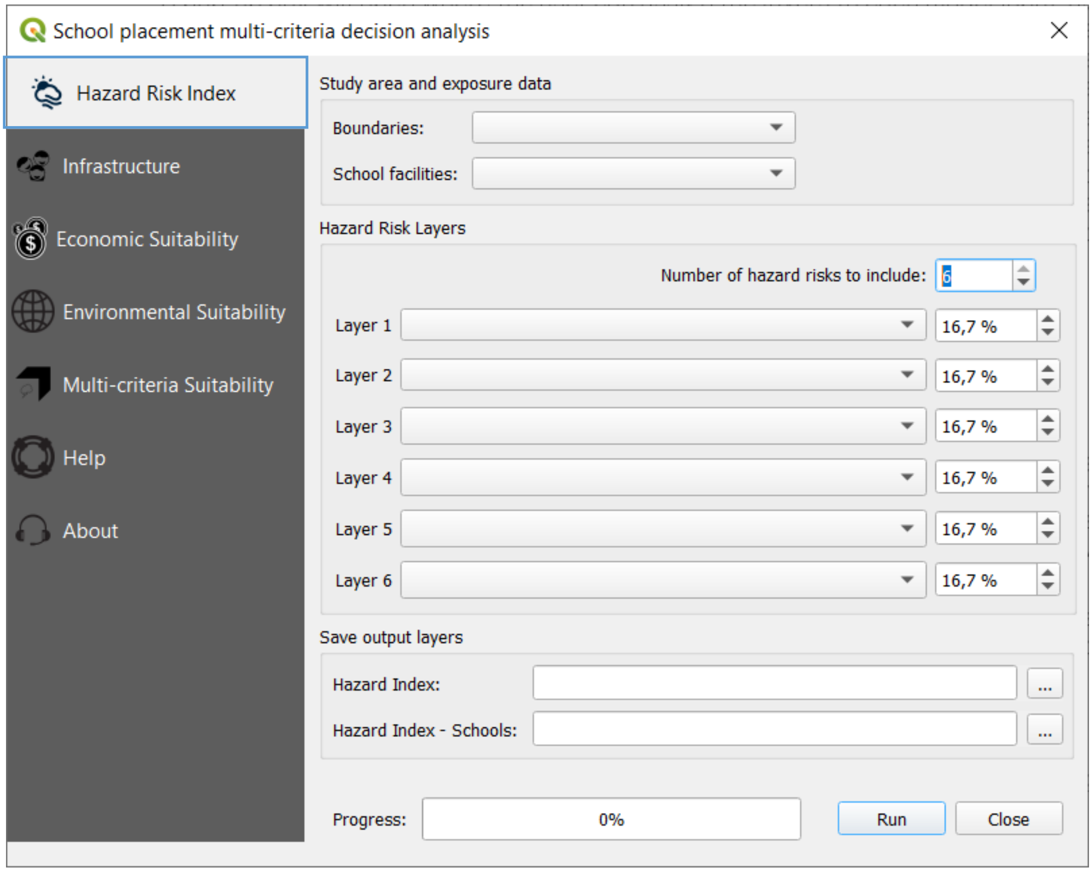
1. Prepare/download all administrative boundaries and data required for the site location and project. These may include the administrative boundaries of the site and country borders.
2. Prepare/download all hazard and exposure datasets. These will include the exposure dataset being measured, for example education facilities or medical facilities, as well as the hazard data, which may include natural hazard risk, conflict hazard, and so on. While for certain countries this information may be readily accessible, for others users may have to rely on freely available high-quality information collected by agencies such as NASA or ESA.
3. Open QGIS. Start a new project and import/load all data into the program. Some files may need to be unzipped first. *Make sure to use a version of QGIS with the GDAL Tools plugin enabled.*
4. Undertake any necessary vector-based analysis on the exposure dataset or supporting data. This may involve clipping data to fit the project area and cleaning up the data as required. The need for this step will depend on the quality and format of the data used.
5. Rasterize, if necessary, the layers used for the hazard analysis. This can be done using the Rasterize tool in the GDAL extension (GDAL > Vector conversion > Rasterize (vector to raster)). Rasterizing converts vector files to raster files. It is important that all layers used for the hazard analysis are raster files so that they can be combined to create the overall hazard risk layer. Note that raster and vector files cannot be combined unless they have first been converted to the same format. Note also that exposure data and boundaries do not need to be rasterized, only hazard layers.
6. Install the ‘School placement multi-criteria decision analysis’ plugin on QGIS. This can be done by opening the ‘Plugins’ menu on the top bar and selecting ‘Manage and Install Plugins’. When this window opens, make sure that ‘All’ is selected in the left-hand column, and type the name of the plugin in the search bar. Once the plugin has been selected, click on the ‘Install Plugin’ button in the lower right corner of the window.
7. Once the plugin is installed, it can be found on the top bar in QGIS or by going to the ‘Plugins’ menu. When opening it, choose the ‘Hazard Risk Index’ option on the left-hand side (outlined in blue in *Figure 4*). Note that all layers need to be already loaded into the program before this step.
    a. For boundaries, select the polygon that delimits the area of analysis. All results will be clipped to fall within it.
    b. For school facilities, choose the point layer representing the locations of schools. The resulting point layer will have the same information plus the sampled value of the hazard risk index.
    c. Choose the number of hazard risk layers to include. This can be any number from 2 to 6. The plugin automatically updates the interface depending on this number.

d. Select the corresponding hazard raster layers. Note that all layers must be pointing in the same direction (i.e. for all layers, a higher score represents more risk while a lower score represents less risk).

e. Specify the weight to give to each layer. Note that these weights must add up to 100%. Since the default number of layers to use in the analysis is 6, the plugin initially displays a weight of 16.7% for each layer (i.e. 100% divided by 6), but this can be changed by the user to any percentage. The choice of weights is of particular importance since it will directly affect the results and their interpretation. Determination of these weights needs to result from extensive consultations with national experts, local stakeholders, and other relevant actors, and should be based on scientific and contextual evidence. Some elements that could guide the discussion are the level of destruction associated with a hazard and the probability of its occurrence.

f. Finally, choose where to save the outputs produced by the plugin, for both the resulting Hazard Index raster layer and the sampled school facilities.

Figure 4. Calculating the hazard index



Source: Authors' own analysis based on the MCDA plugin.

8. Once the model is completely specified, click on 'Run'. This will launch the calculations, which will produce two output layers. These can then be rendered into symbols to display, using cartographic elements, the risk at each education facility location (point vector layer), and the overall hazard index or site area (raster layer), for example using a green-to-red colour scale bar to represent low risk (green) to high risk (red).

9. The generated map can be exported to an image, shared online, or published as a web map or layer. The attribute information can also be exported in CSV format and analysed further in Excel.

1.4. EXAMPLE: INDONESIA

To illustrate the method outlined in *Figure 3* and *Figure 4*, we perform the analysis and present the findings for Aceh Province in Indonesia, using the same steps.

1. All relevant general data were downloaded from the HDX website, and the hazard risk assessment data were downloaded from the InaRISK data portal (BNPB, 2021). The relevant natural hazard risk layers were imported from an ArcGIS service directory from InaRISK directly into QGIS as web coverage services (WCS) or raster layers and then exported to the local drive.
2. The education facility locations (exposure data) in Sumatra were downloaded from the HDX website (OCHA, 2019).
3. QGIS was installed and opened, and all the data were loaded in.
4. Necessary vector-based analysis was performed to clip the Indonesia administrative boundaries to only Aceh Province for the output boundary. Aceh Province was selected from the Provincial ADM0 layer and exported by right-clicking on the layer and selecting *Export > Save Selected Features As.*[4] This saves Aceh Province only as its own new layer.
5. All the data were already in the requisite format, so there was no need for any data to be rasterized.
6. The plugin was installed on QGIS using the 'Install and Manage Plugins' option under the 'Plugins' menu.
7. The Hazard Risk Index was then run using the layers presented in
8. Table 5. A visual representation of the different calculations performed by the algorithm is given in *Figure 5*.

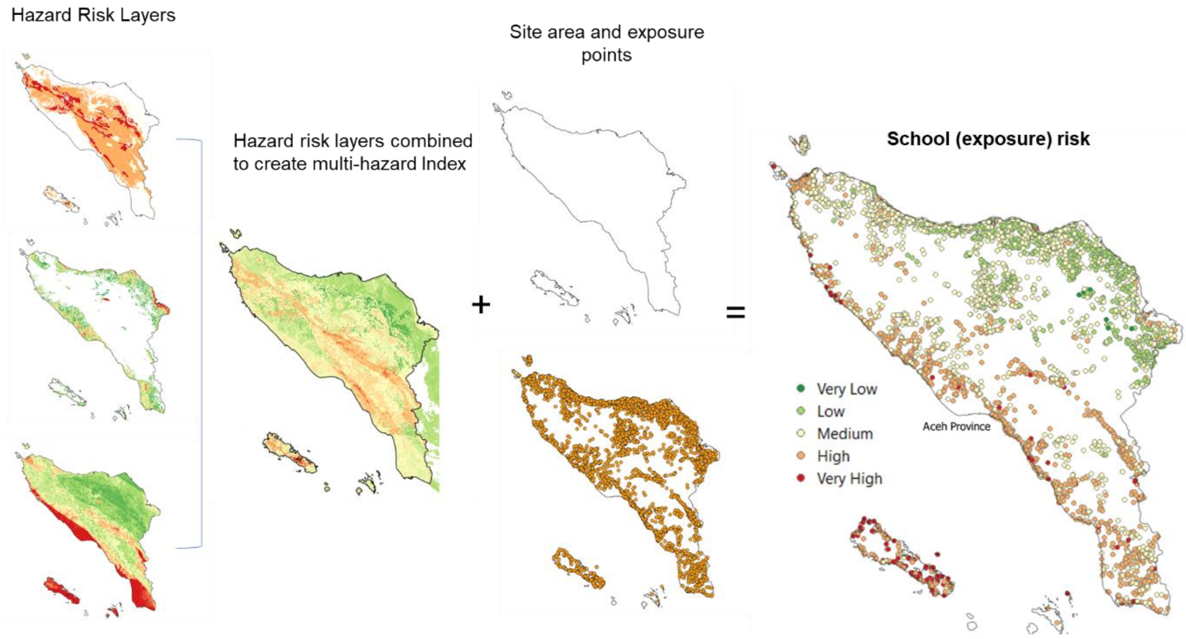
Table 5. Layers used to calculate the hazard index

Layer type	Layer name	Source	Weight
Hazard layer 1	Earthquake hazard	InaRISK portal: INDEKS_BAHAYA_GEMPABUMI	40%
Hazard layer 2	Flood hazard	InaRISK portal: INDEKS_BAHAYA_BANJIR	20%
Hazard layer 3	Tsunami hazard	InaRISK portal: INDEKS_BAHAYA_TSUNAMI	10%
Hazard layer 4	Severe weather event	InaRISK portal: INDEKS CUACA EKSTRIM	5%
Hazard layer 5	Landslide	InaRISK portal: INDEKS_BAHAYA_TANAH_LONGSOR	20%
Hazard layer 6	Volcano	InaRISK portal: INDEKS_BAHAYA_GUNUNGAPI	5%
Exposure sites	Indonesia education facilities	HDX	N/A
Site location	Aceh administrative area (layer as analysed in Step 4)	HDX	N/A

Source: Authors' own analysis using names from BNPB (2021) and OCHA (2019, 2020).

[4] ADM0 is the name of the layer downloaded from HDX.

Figure 5. Example breakdown of graphical model in *Figure3*



Source: Authors' analysis with QGIS.

9. The output layer was symbolized using coloured dots to represent the level of risk for each education facility location. The overall multi-hazard risk layer was also stylized.

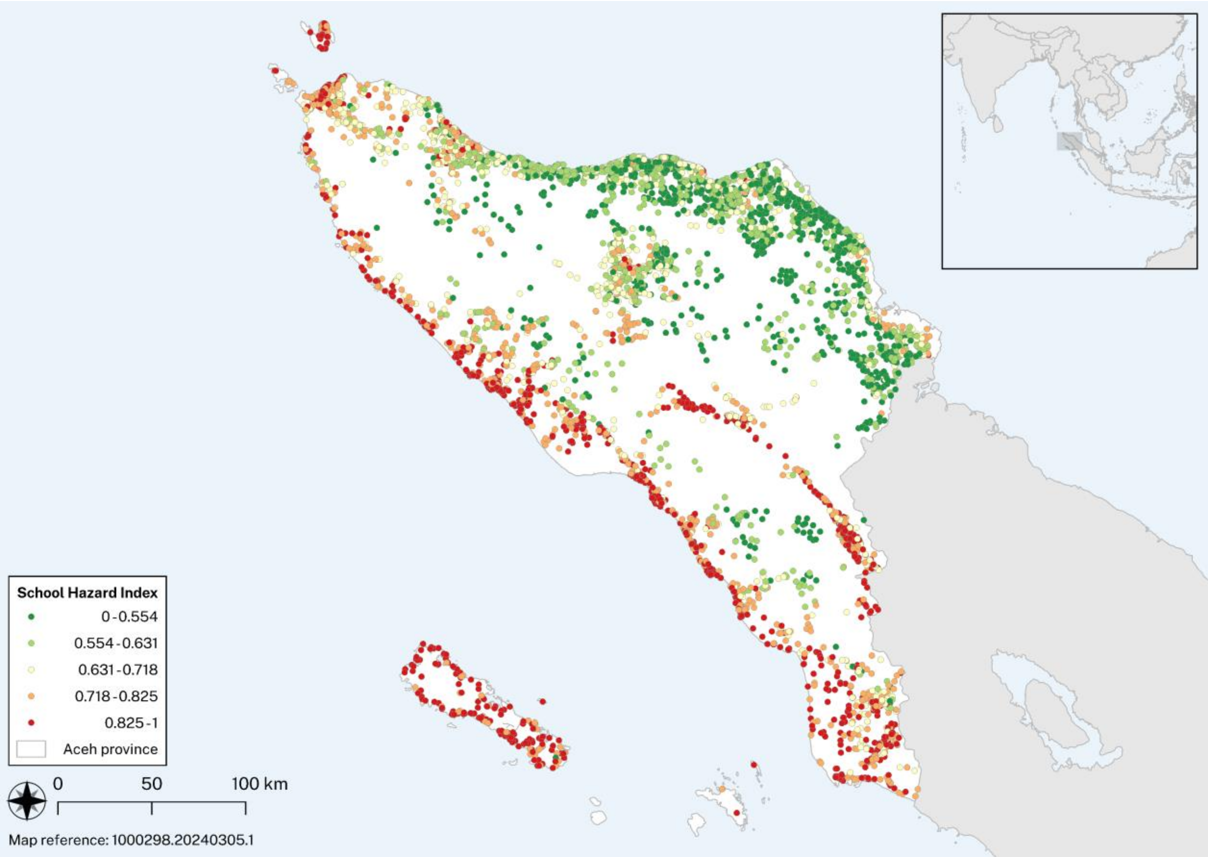
10. The two resulting maps are shown in *Figure 6* and *Figure 7*.

1.4.1. Outputs

Once the Hazard Risk Index algorithm is run, the results are visualized as maps like those in *Figure 6* and *Figure 7. Figure 6* shows values of the projected multi-natural hazard and exposure index for schools in Aceh Province, Indonesia. These values were obtained by sampling the average values of the resulting overall multi-hazard natural risk index and the locations of schools.

In this example for Aceh Province, the highest weights were assigned to earthquakes, landslides, and floods. The south coast and the big island south of the province are the areas are most affected by these hazards and more exposed to them, whereas the northern part of the province, particularly the northeast quadrant, has low exposure to these hazards. It also appears that some schools located very close to one another have different risk profiles. This is due to the size of the points and the sheer number of schools in the region (5,259 schools in Aceh). *Figure 7*, which has a higher resolution, shows that the mountainous characteristic of the region causes scores to vary according to location relative to valleys and mountains (in particular for landslide and flood risks).

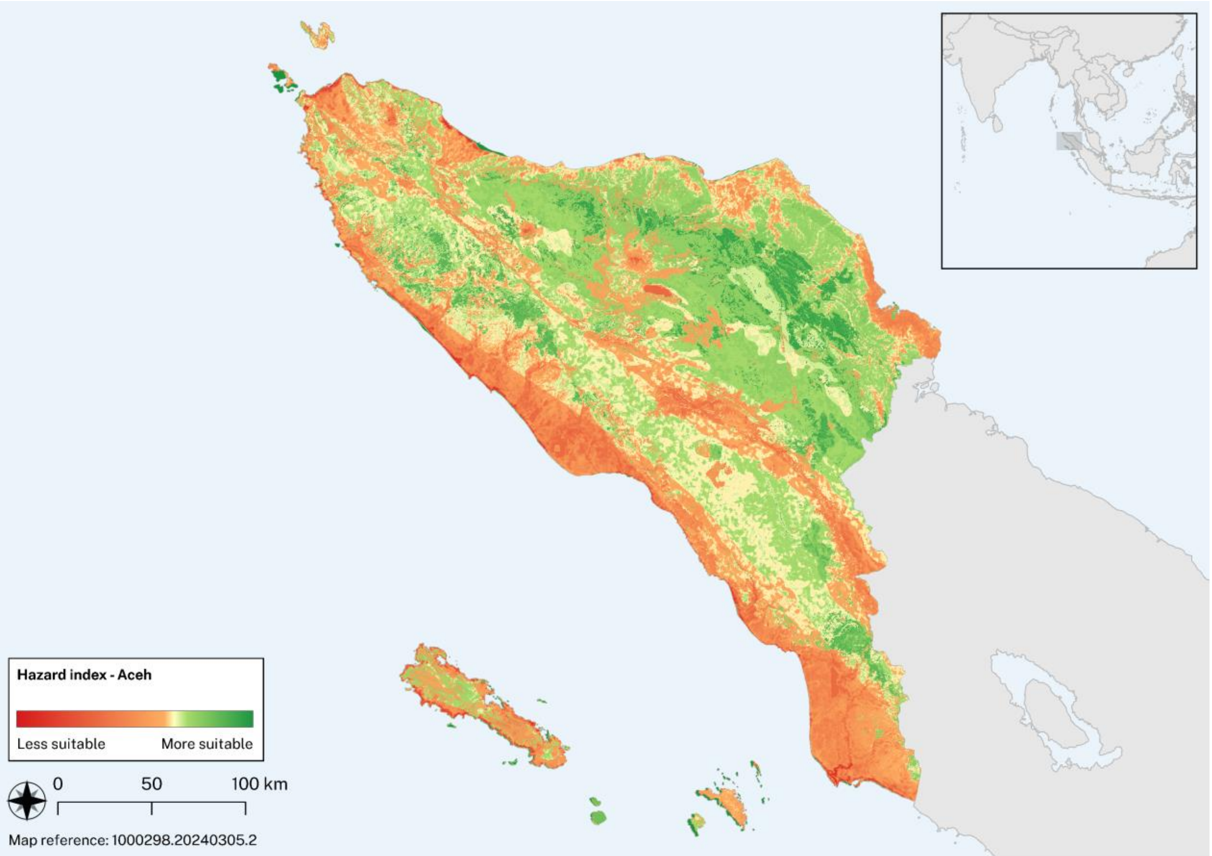
Figure 6. Risk index for each education facility in Aceh Province



Source: Authors' own analysis with QGIS using data from InaRISK (2021) and HDX (2019).

It is also seen in *Figure 7* that the low-lying lands in the northeast have lower hazard indexes, while the mountain chains to the south and west, as well as the mountainous island, score higher. The very clear line of transition from green and yellow dots to red dots is due to, among other factors, the way seismic frequency is coded by the InaRISK portal. This highlights again the importance of data quality and granularity, and how these factors can influence the results of the analysis.

Figure 7. Overall multi-hazard risk for Aceh Province



Source: Authors' own analysis with QGIS using data from InaRISK (2021) and HDX (2019).

2. MULTI-CRITERIA DECISION ANALYSIS MODEL

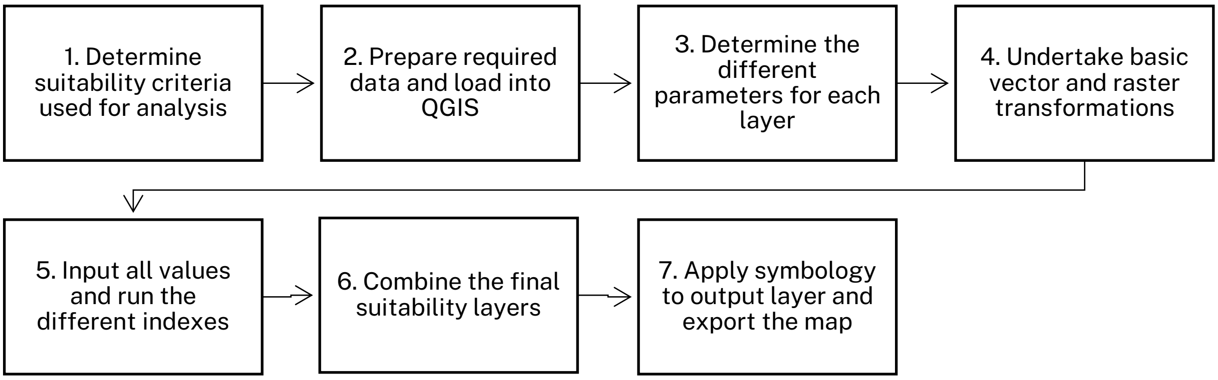
Part 1 of this technical note presented a multi-hazard risk index and demonstrated its calculation for the example of Aceh Province in Indonesia, based on prevalent natural hazards in the region. This hazard index helps to identify education facilities located in hazard-prone areas. *Part 2* develops a MCDA model for identifying areas that are more suitable for new education facilities to be located, based on a range of nationally defined criteria and hierarchical weighted additions. In extreme cases, this method could aid in identifying safer locations to which existing schools could be relocated, should their maintenance or upgrade be impossible. *Part 2* uses the output of *Part 1* as one of its inputs, as explained in the following sections.

When conducting this analysis, several parameters (the 'criteria') must be specified based on the site suitability requirements (i.e. what each national or regional authority defines as the criteria for a location to be suitable for the construction of a new school). These suitability criteria are customizable and can be adjusted depending on the example under consideration. *Part 2* continues the analysis of *Part 1* and uses the same example of Aceh Province, Indonesia.

2.1. METHODOLOGY

Figure 8 outlines the steps in the MCDA procedure. The method makes use of several customized geospatial graphical models and one of the outputs from *Part 1*. The methodology is explained step by step using the example from Indonesia.

Figure 8. Method developed for calculating the site suitability of new education facility sites



Source: Authors.

2.2. EXAMPLE: INDONESIA

Step 1. Determine suitability criteria to be used for the analysis

Before undertaking the analysis, the suitability criteria and parameters need to be determined in accordance with site indicators, national legislation, and local knowledge and expertise, all while keeping data availability in mind. These site suitability criteria are spatial indicators that contribute to calculating the suitability of a particular location and include factors such as distance to roads, distance to waterways, distance to buildings, and hazard risk. The suitability analysis determines which criteria and categories are used.

Usually, the criteria for the analysis are first grouped into broader categories and then broken down into specific indicators. For the Indonesia example, seven criteria under three categories are selected, in line with the Indonesian context, the relevant literature (Bukhari, Rodzi, and Noordi, 2010; Jamal, 2016), and data availability. The seven criteria are grouped into three categories and include environmental and hazard factors, infrastructure and economic factors, and social factors, as outlined in *Figure 9*. Note that while the different elements included in the MCDA model are flexible enough to be applied to a range of countries and regions, sometimes additional elements may be needed to comply with national or local legislation, or to better take into account environmental, infrastructure, and economic factors. If that is the case, a request can be made by email to IIEP to tailor the model to a particular set of constraints. Note also that elements included in Category 3 are based on the traditional methodology of micro-planning, dating back to the 1970s and 1980s (Caillods et al., 1983; Hallak, 1977). However, the inclusion of elements in Categories 1 and 2 expands and complements this initial approach, enriching the analysis and allowing the educational planner to make more informed decisions.

Figure 9. Example of criteria selected for the example of Aceh Province, Indonesia

Category 1: Environmental and Hazard Criteria

- Multi-hazard risk assessment, conducted in Part 1, to display the risk level.
- Slope risk, to ensure building safety and mitigate hazard risk.
- Vegetation disruption, to minimize tree and forest disruption in building/constructing an education site.

Category 2: Infrastructure/Economic Criteria

- Main road proximity, to ensure that schools are not located too close or too far from main roads, for noise and safety reasons.
- River and flash flooding risks (minimal watershed impacts), to ensure that the site will not be located within a flood zone.

Category 3: Infrastructure Criteria

- Population density, to ensure that schools will be located within populated areas for usability and accessibility by the population.
- Existing education facilities, to ensure that new education facilities constructed are well spaced out between existing education facilities for optimum usage.

Source: Authors' own analysis with inputs from relevant literature.

Step 2. Prepare/download required data and load into QGIS

Once the criteria are selected, the relevant data need to be prepared. Preference should be given to nationally produced official data, as this would guarantee that national data quality standards are met and would foster data and procedural ownership of the analysis on the part of local officials. When national data are not available, or when doubts exist regarding the reliability of this information, several sources on different topics are freely accessible. Some useful open-source websites were listed in *Section 1.2*. The various data sources used for the Indonesia example are presented in *Table 6*. Keep in mind that the greater the number of categories and the larger the area, the more data need to be processed and hence the slower the processing will be.

Table 6. Data sources for the Indonesia example

Category	Criteria	Description	Source (and corresponding Reference)
Environmental suitability	Multi-hazard risk	Multi-hazard risk layer as calculated in *Part 1*	InaRISK (BNPB, 2021)
	Slope risk	Slope risk calculated from a digital elevation model (DEM)	NASA SRTM (Shuttle Radar Topography Mission) 30-metre-resolution elevation data (Watkins, 2021)
	Primary forest area	Major forest areas combined to create one primary forest area	Global Forest Watch, World Resource Institute (Global Forest Watch, 2019)
Economic suitability	Road locations	Main roads extracted only	HDX, OSM (OCHA, 2021a)
	River and water bodies	Locations used to calculate river and flash flooding risks	HDX, OSM (OCHA, 2021b)
Infrastructure	Population density	Population density, 2020	WorldPop (WorldPop, 2018)
	School locations	Same layer as used in *Part 1*	HDX, Indonesian Government (OCHA, 2019)

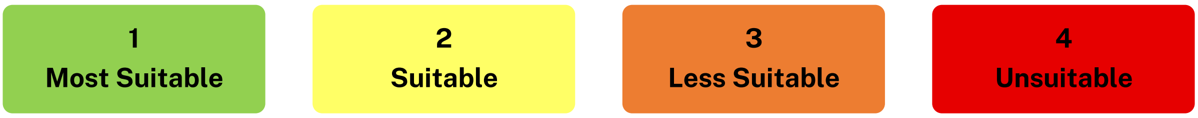
Source: Authors' analysis. See References section for further information.

While it is generally good practice to have all data layers in the same projected reference system, the model allows for heterogeneity in this respect. It is important, nevertheless, to decide on the appropriate projected reference system (PRS) to use. This is because many of the internal computations performed by the different geospatial graphical models rely on calculations in metres, which are possible only when working with a PRS, as opposed to a geographical reference system (GRS). Since the PRS changes depending on the region being analysed, it must be set by the user, who can type in the name of the country to search for the appropriate PRS.

Step 3. Determine the different parameters for each layer

As data coming from multiple sources will be classified differently, it is essential to create a streamlined classification system that can be used to calculate the suitability. The easiest way to do this is by using a ranking system. For this model a ranking system of 1 to 4 is used to represent areas that are most to least suitable, as shown in *Figure 10*.

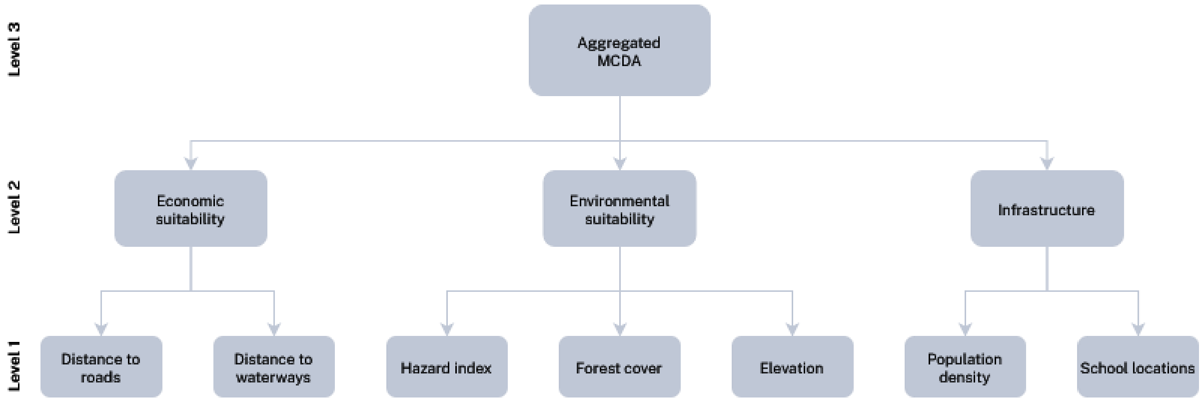
Figure 10. Suitability ranking



Source: Authors.

This weighted additions model is highly customizable, allowing users to specify their preferences at three different levels, as shown in *Figure 11*. At Level 2, the user can specify the weight to assign to each of the three elements that make up the aggregated MCDA (economic, infrastructure, and environmental suitability). The same is true within each of these three elements, with users being able to determine the relative importance of each of the components in Level 1 for each of the categories in Level 2. For instance, for a particular country it might be relevant to give ‘Hazard index’ and ‘Forest cover’ greater weights than ’Elevation’, because the country is prone to flash floods and covered in forests but is relatively flat. In that case, it might be suitable to allocate 0.4 each to Hazard index and Forest cover and just 0.2 to Elevation.

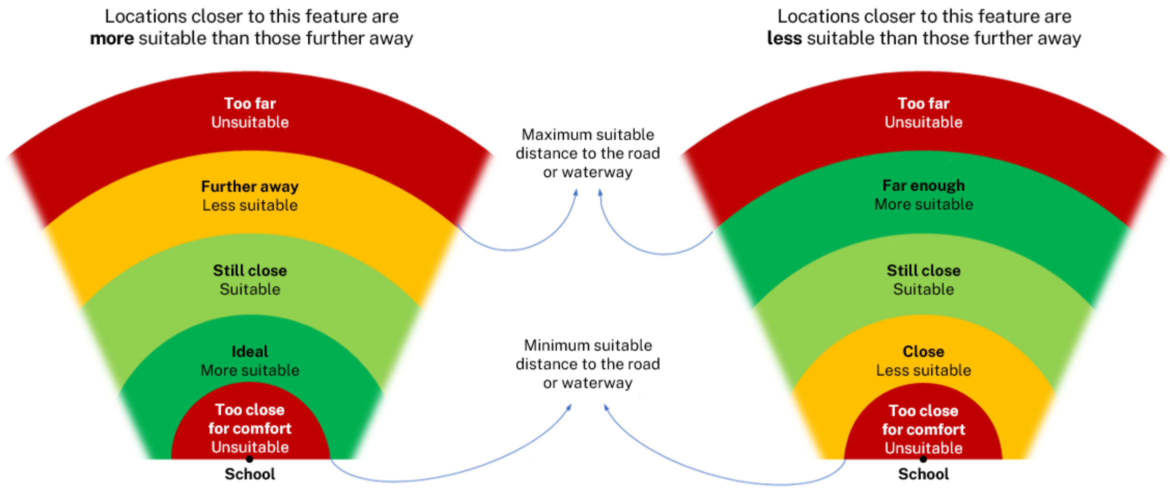
Figure 11. Different levels of customization possible in the model



Source: Authors.

A third, more micro, level of customization is also possible. For some variables in Level 1, the choice of what is suitable and what is not can be directly specified in the model. For example, when running the model for ‘Economic suitability’, the user must specify for roads and waterways whether schools are more or less suitable in relation to their distance to these variables, as shown in *Figure 12*. In a country prone to flash floods, for instance, it would be better to locate schools further from rivers and canals, while the opposite might be true for countries where rivers and canals are sources of water for drinking or cooking, or means of transportation for students and staff.

Figure 12. Assigning suitability scores depending on the local context



Source: Authors.

Finally, the user can determine what is considered too close or too far for each variable. The model will automatically determine the partitions by following the rules shown in *Table 7*. In other words, *Table 7* presents the rules that determine the boundaries between each of the differently coloured areas in *Figure 12*. Note that it is possible to specify a minimum distance of 0 if there are no restrictions related to proximity to a particular attribute.

Table 7. Rules for assigning suitability scores based on minimum and maximum distances and allocation preference

Lower bound	Upper bound	Locations close to this feature are more suitable that those further away	Locations close to this feature are less suitable that those further away
Distance < Min		Unsuitable	Unsuitable
Distance ≥ Min	Distance < Max × 1/3	More suitable	Less suitable
Distance ≥ Max × 1/3	Distance < Max × 2/3	Suitable	Suitable
Distance ≥ Max × 2/3	Distance < Max	Less suitable	More suitable
Distance ≥ Max		Unsuitable	Unsuitable

Source: Authors.

Since these models use a variety of data sources, it is important to harmonize them into a stable, comparable scale, so that their aggregation will yield sensible, interpretable results. Each model automatically does this, by classifying each layer into the same 1–4 scale as shown in *Figure 10*.

All the data used in this example, listed in *Table 6*, were analysed and classified based on appropriate geospatial parameters for each dataset.

As the model is highly customizable, we recommend that different criteria scores are set up to suit the objective of each example. *Table 8*Table 8 outlines the choices made in each layer for the Indonesia example. Setting up such a table and assigning a score to each criterion is very important and should be the result of concerted discussion with multiple national, regional, and local experts on educational planning, climate change, and crisis preparedness. Each criterion does not have to include all the scores of 1, 2, 3, and 4; certain variables (e.g. tree cover) are dichotomous and so are assigned only two scores, 1 (no forest) or 4 (forest).

Table 8. Criteria scores used for the suitability analysis

Category	Criteria	Score	Suitability
Environmental suitability	Multi-hazard risk index, as calculated in *Part 1*		
	[0–1)	1	More suitable
	[1–2)	2	Suitable
	[2–3)	3	Less suitable
	[3–4]	4	Unsuitable
	Slope		
	[0–1)	1	More suitable
	[1–10)	2	Suitable
	[10–20)	3	Less suitable
	≥20	4	Unsuitable[a]
	Tree disruption, primary forest		
	No clearing needed	1	Most suitable
	Clearing of primary forest needed	4	Unsuitable
Economic suitability	Distance from main roads[b]		
	≥500 m	4	Unsuitable
	[333–500 m)	3	Less suitable
	[166–333 m)	2	Suitable
	[20–166 m)	1	More suitable
	[0–20 m)	4	Unsuitable[c]
	Distance from waterways (rivers and streams)[d]		
	≥1,500 m	4	Unsuitable
	[1,000–1,500 m)	3	Less suitable
	[500–1,000 m)	2	Suitable
	[150–500 m)	1	More suitable
	[0–150 m)	4	Unsuitable
Infrastructure	Proximity to existing schools[e]		
	≥1,500 m	1	More suitable
	[1,000–1,500 m)	2	Suitable
	[500–1000 m)	3	Less suitable
	[0–500 m)	4	Unsuitable
	Population density[f]		
	Within population centre	1	More suitable
	Outside population centre	4	Unsuitable

Source: Authors' analysis.

See footnote for explanation of notes.[5]

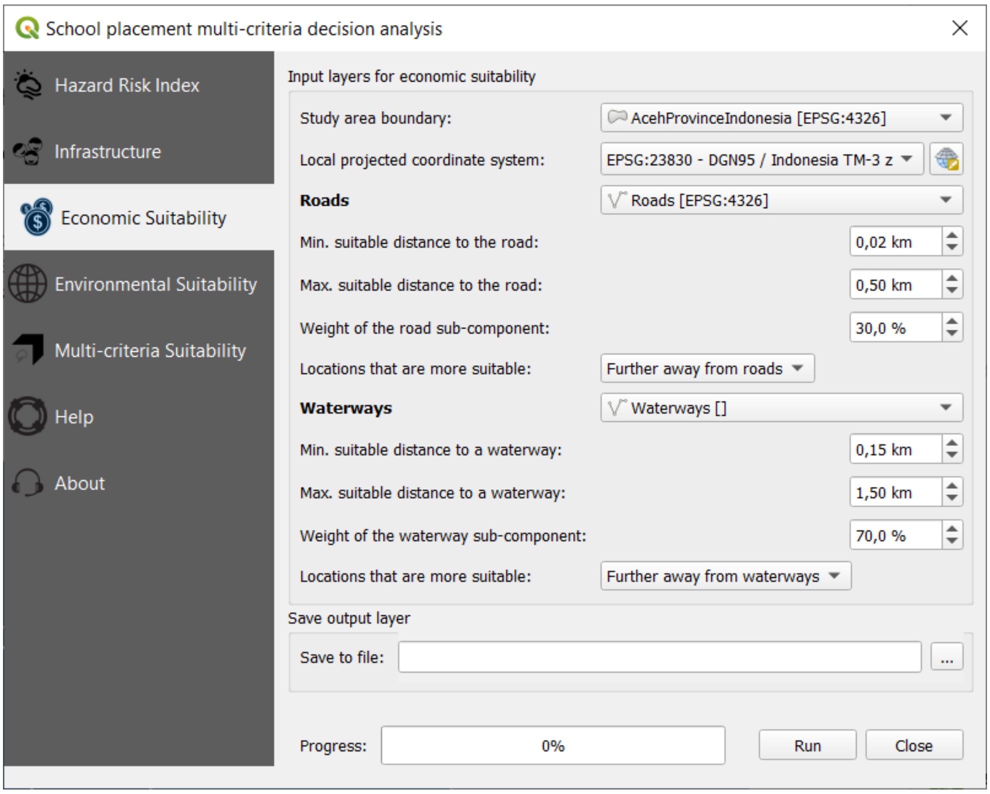
Step 4. Undertake basic vector and raster transformations

Once all the data are loaded into QGIS, basic data transformations may need to be undertaken. These may include editing or deleting fields and separating relevant data from unnecessary data. For example, in the Indonesia example the Roads layer was processed to ensure that only main roads, highways, and secondary roads were included in the analysis, while smaller roads were removed. For raster files, the only modification needed is to make sure that 'Forest cover' (or 'Desert cover') is a dichotomous variable where 0 indicates no cover and 1 the presence of cover. If another distribution exists, the GDAL raster calculator algorithm can be used to obtain the corresponding dichotomous raster layer.

Step 5. Input all values and run the different indexes

After completing the previous steps, the user can run the algorithms for economic, environmental, and infrastructure suitability, making sure to follow the different instructions for each of the algorithms. *Figure 13* shows an example for the section on economic suitability for the Aceh Province case.

Figure 13. Economic suitability model for the Aceh Province example



Source: IIEP-UNESCO, GISPO: MCDA plugin in QGIS (2022).

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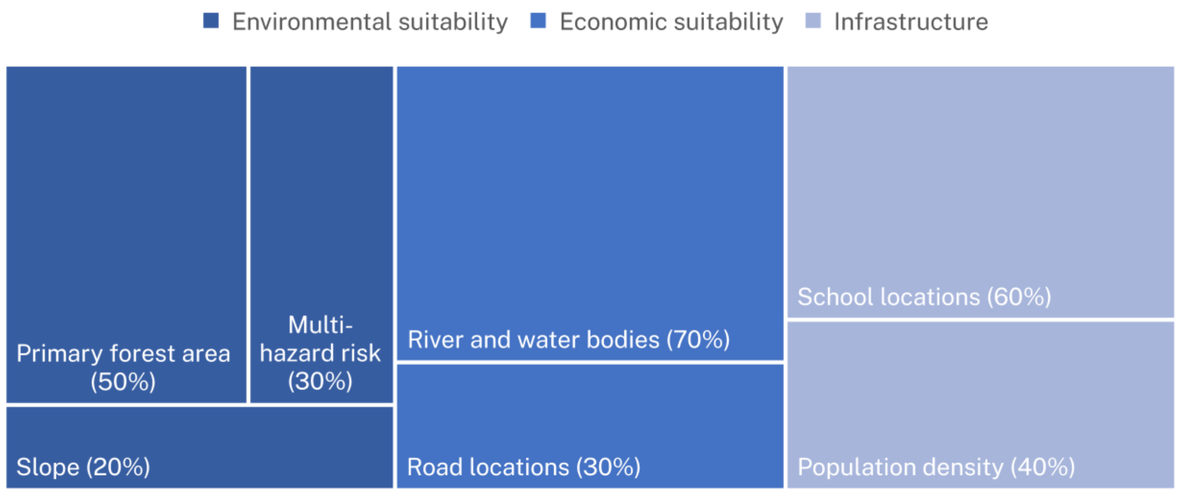
[5] **a.** The unsuitability of steep slopes is contextual; for example, the education systems in countries such as Rwanda and Switzerland have developed building techniques which guarantee that schools are suitable even in high-slope contexts.
b. Suitability is based on the assumption that schools can be close to the road network but with a minimum distance of 20 metres to avoid issues of traffic, pollution, and noise.
c. As with the maximum slope, the minimum distance to roads is context dependent and can be changed to 0 if necessary; for example, in France most preschools and primary schools are located next to roads without any issues.
d. Suitability is based on the assumption that given the usefulness of rivers and streams as a means of transportation and as a water source, schools are better off being close to waterways than farther away; however, a minimum buffer of 150 metres is preferred, to avoid problems during floods and the rainy season.
e. Priority should be given to locations that are not currently close to other existing schools.
f. In this model, emphasis is placed on urban areas over rural areas; however, this is not always appropriate, and whether to give preference to urban or rural areas should be decided in concerted discussion with relevant stakeholders.

Once these algorithms are run, the user will have three raster layers, each with values ranging between 1 (most suitable) and 4 (least suitable). In the Aceh Province example, the weights used were those presented in *Figure 14*. Note that for each category the weights add up to exactly 100%. In real life, the decision of the weights to use should be the result of a lengthy process of discussion, evidence reviews, collation of knowledge from local experts, and so on.

Figure 14. Weightings of the criteria used for the Aceh Province example



Source: Authors' own analysis.

Step 6. Combine the final suitability layers

After all the suitability layers have been created, the MCDA model is ready to be run. As with the previous suitability algorithms, the user must determine the relative weights for the three layers (with the three weights adding up to 100%). Once these weights are selected, the user can run the model to obtain the final suitability results that capture the three subcomponents with the custom parameters. For the Aceh Province example, the weights used are presented in *Table 9*.

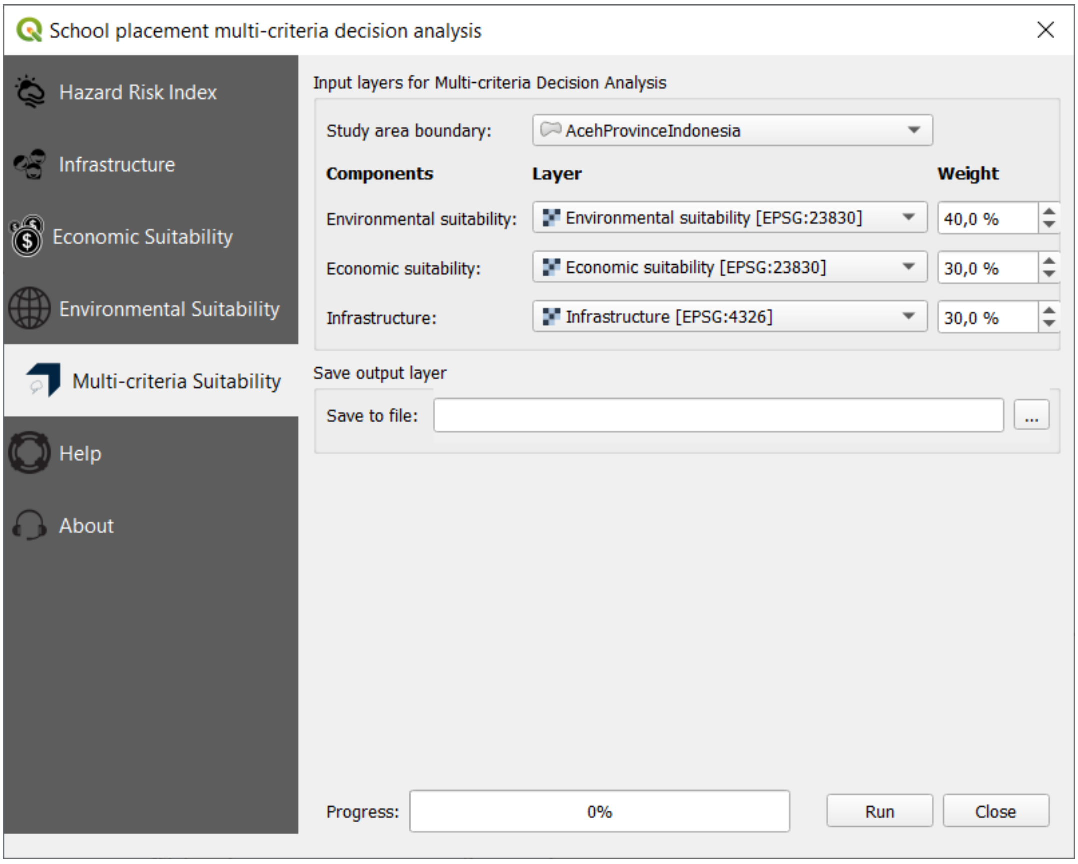
Table 9. Weightings of the three categories used in the Aceh Province example

Category	Weighting
Environmental suitability	40%
Economic suitability	30%
Infrastructure	30%

Source: Authors' own analysis.

The setup of the MCDA geographical model in QGIS, with the weights presented above, is shown in *Figure 15*.

Figure 15. MCDA model for Aceh Province, Indonesia



Source: Authors.

Step 7. Apply symbology to output layer and export the map

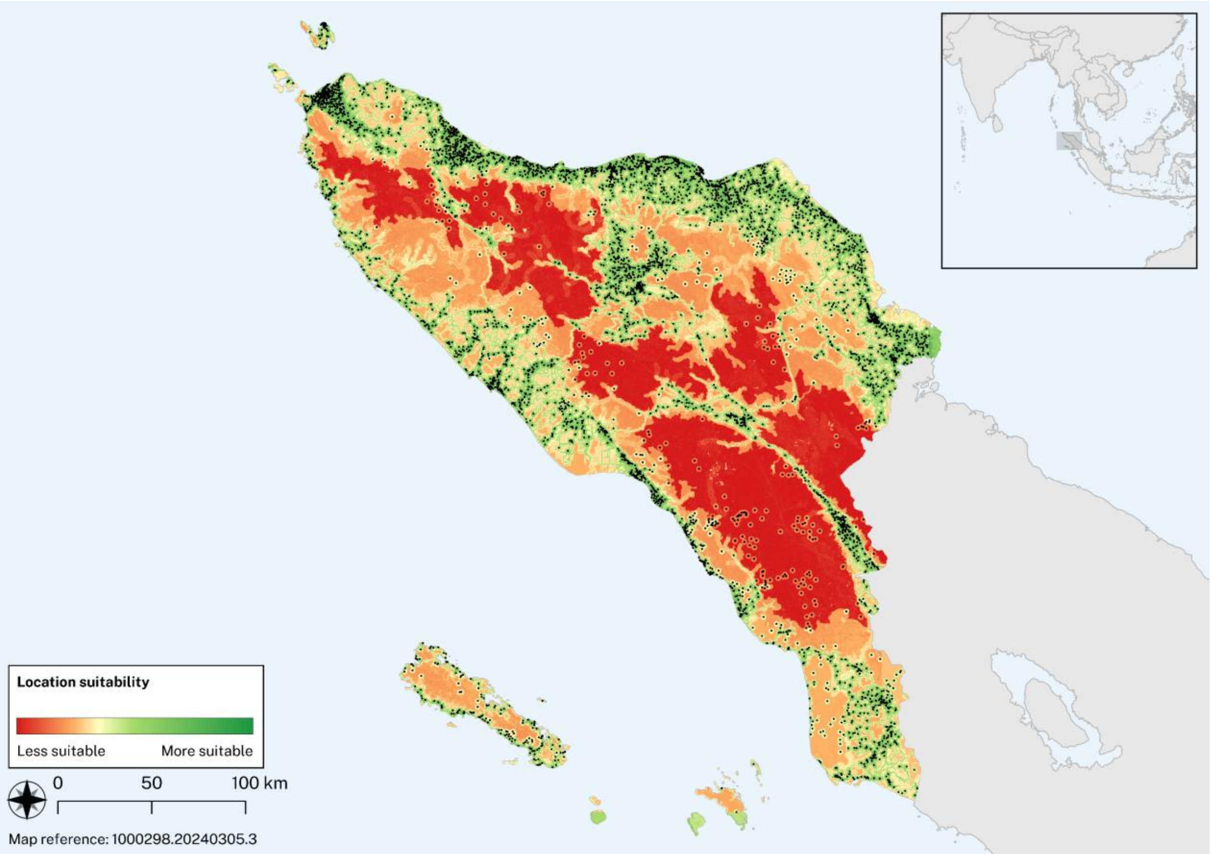
Since the resulting raster layer from the MCDA calculations is by default presented as a monochrome layer, the layer symbology should be changed to help with interpretation and shareability. To do this, we recommend to using a *Singleband pseudocolour* scale, making sure to note that lower scores are associated with places that are more suitable for schools, while high scores indicate unsuitable places.

2.2.1. Outputs

The results of the analysis in *Part 2* for the Aceh Province example are presented in *Figure 16* and *Figure 17. Figure 16* displays the raster map showing the suitability analysis for the relocation of existing schools or the construction of new education facilities based on the multiple risks included in the model. *Figure 17* presents the same information but zooming in on an area of the Province, so that it is easy to see which schools are in unsuitable or less suitable areas in the region analysed.

As with the example in *Part 1*, the choice of weights greatly affects the results of the analysis. In this case, 'Forest cover' has a very high weight. This, together with the fact that it begins as a dummy variable that gets codified as 0 if there is no forest and 4 if there is, makes the result stand out in both maps.

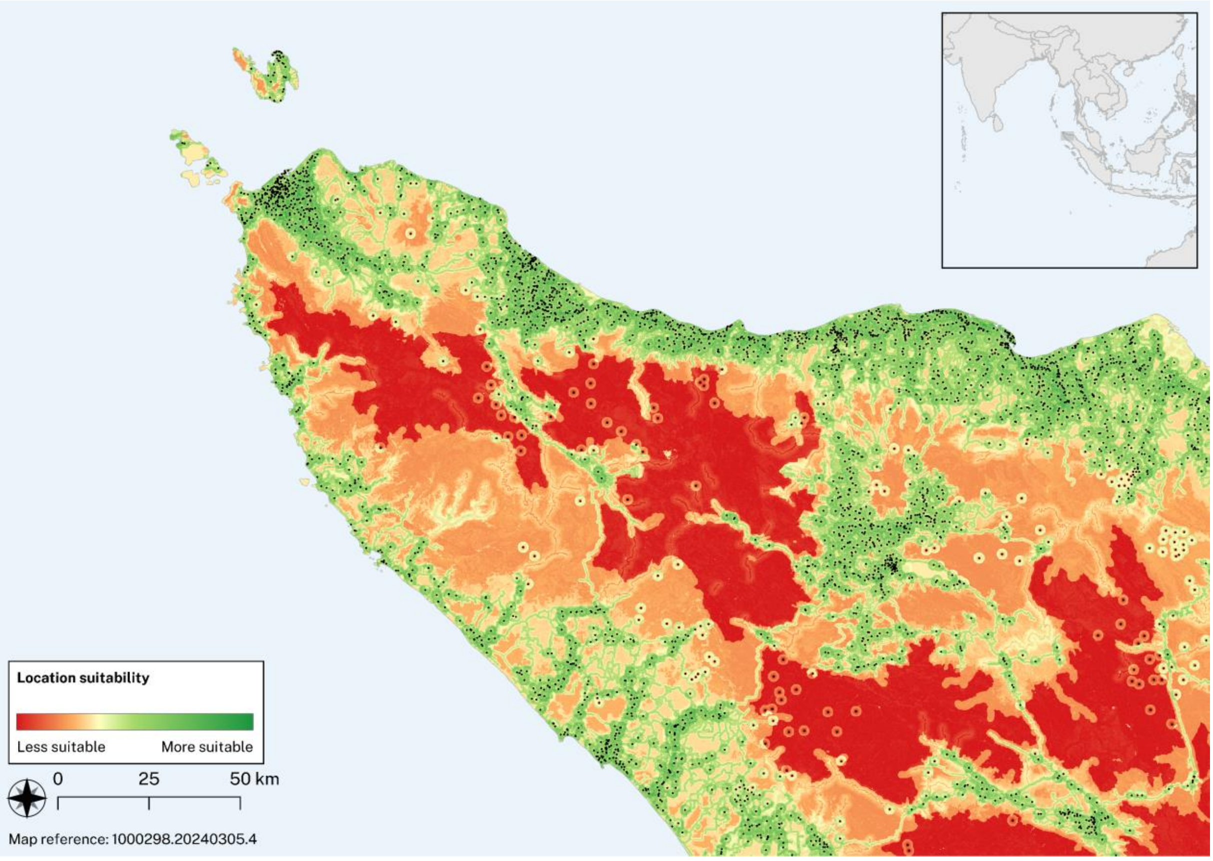
Figure 16. Suitability map for relocation and construction of education facilities in Aceh Province, Indonesia



Source: Authors' own analysis with QGIS using data from InaRISK (2021), HDX (2019), NASA (2021), WorldPop (2018), OSM (2021), and Global Forest Watch (2019).

Upon zooming in on a region, pockets of suitability can be seen around schools, rivers, and roads; this again is in line with the different specifications included for the model. This is especially evident in the red (i.e. less suitable) areas, where schools have small pockets of suitable terrain around them. This reinforces the principle that the choice of parameters for the model needs to be the result of a lengthy process of dialogue with multiple stakeholders, spanning different administrative levels, and taking into consideration expert opinions, and so on, so that the results will be relevant for the region or country in question.

Figure 17. Zoomed-in view of suitability map for relocation and construction of education facilities in Aceh Province, Indonesia



Source: Authors' own analysis with QGIS using data from InaRISK (2021), HDX (2019), NASA (2021), WorldPop (2018), OSM (2021), and Global Forest Watch (2019).

3. CONCLUSION

Schools cannot be understood apart from their environment. This fact underlines the need for planners to lead context-based environmental analyses for educational infrastructure, as well as taking a multi-tiered approach to the analysis of suitable locations for the construction of new schools or the refurbishment of existing ones.

This technical note outlines a methodology and provides an example of the use of open-source tools and data sources for infrastructure planning and maintenance, within the context of geospatial data for educational planning. It presents an index to inform planning and interventions that can factor in infrastructural, economic, and environmental considerations. The methodology and its associated analyses are not meant to replace political and economic debates on school construction and refurbishment but rather to furnish inputs to such debates based on geospatial and satellite-derived data.

Users of the methodology should always acknowledge the limitations of the data and method and take these into consideration by supplementing where possible with ground and field-based observations, data, and knowledge. The methodology presented here should be used together with other decision-making tools and practices – such as ground truthing, political and social dialogue, or educational demand simulation models – to provide an overview or snapshot of a specific location and suggestions of potential avenues for educational policymaking.

Combined with EMIS information on infrastructure – such as school location, building materials, damage, classroom furniture, amenities, access to drinking water, electricity supply, availability of kitchen and canteen – the methodology can be used to identify which schools to prioritize in a maintenance scheme or school improvement programme, or to provide vulnerability data to further inform crisis-sensitive planning.

The methodology can also help civil society actors, NGOs, and other stakeholders to plead their case for schools being built or refurbished in particular cities or villages.

At its core, the methodology is based on the concepts and logic underlying traditional micro-planning and school mapping. As such, it is an extension of the basic tools that educational planners have been using for decades and can thus enrich existing analyses and practices. We expect this to be especially useful in planning for the future, with the acceleration of human-induced climate change and the challenges that entails for education systems around the world (such as the increase in the frequency and power of natural disasters and extreme climatic events). The model's flexibility means that the particularities of each country or region can be taken into account and the model adjusted as circumstances change.

The methodology is flexible and can be expanded by interested stakeholders. All documentation, including the source code, is freely available, and the development team at IIEP-UNESCO remains available to respond to requests for modifications and extensions.

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