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Technical note

RePlant Alfa: Integrating Google Earth Engine and R coding to Support the Identification of Priority Areas for Ecological Restoration

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Abstract: Land degradation and climate change are among the main threats to the sustainability of ecosystems worldwide. Therefore, the restoration of degraded landscapes is essential to maintain the functionality of ecosystems, especially those with greater social, economic and environmental vulnerability. Nevertheless, policy-makers are frequently challenged by deciding on where to prioritize restoration actions, which usually includes to deal with multiple and complex needs under an always short budget. If these decisions are not taken based on proper data and processes, restoration implementation can easily fail. To help decision-makers taking informed decisions on where to implement restoration activities, we have developed a semiautomatic geospatial platform to prioritize areas for restoration activities based on ecological, social and economic variables. This platform takes advantage of the potential to integrate R coding, Google Earth Engine cloud computing and GIS visualization services to generate an interactive geospatial decision-maker tool for restoration. Here, we present a prototype version called "RePlant alpha" which was tested with data from the Central Zone of Chile. This exercise proved that integrating R and GEE was feasible, and that the analysis, with at least six indicators and for a specific region was also feasible to implement even from a personal computer. Therefore, the use of a virtual machine in the cloud with a large number of indicators over large areas is both possible and practical.

Keywords: Google Earth Engine; R coding; GIS; Restoration; Decision-Making

1. Introduction

Land transformation and soil degradation are among the greatest threats to the resilience of ecosystems worldwide (Steffen et al, 2015). Thus, developing strategies to help restoring degraded ecosystems is an urgent task that will help keeping the planet in healthy ecological conditions to support biodiversity, tackle climate change, and promote human development (Abhilash, 2021). In fact, The United Nations has made an explicit call to implement restoration activities, naming the 2021-2030 the "UN Decade on Ecosystem Restoration" (www.decadeonrestoration.org). Nevertheless, developing restoration activities will be challenging, particularly when they need to be intertwined with a myriad of other uses in socio-ecological landscape mosaics (Aronson, 2020). Under these circumstances, it is key to identify areas that are likely to maximize the benefit provided by restoration and minimize social and economic costs of implementation (Brancalion et al, 2019).

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Hence, developing tools to help overcome the challenges of implementing restoration activities in socio-ecological landscapes is key to increase the effectiveness of a country's specific actions.

One of the main challenges to identify the best areas to implement restoration activities is the large number of variables that need to be jointly assessed, which usually include ecological, economic, social and institutional factors (Morales et al. 2021). Spatial prioritizations like this could be addressed with the use of Multi-Criteria Spatial Decision Analyses, which integrate different geospatial variables through a system of interaction rules that combine them to generate information for decision-making (Mendoza & Martins, 2006; Malczewski 2006; Huang et al. 2011). Such an approach has been recently proposed to identify global priority areas for restoration (Strassburg et al, 2020), and has been also used for prioritizing areas for restoration at finer scales (e.g. Orsi & Geneletti 2010; Vettorazzi & Valente 2016; Fernández & Morales 2016).

However, a pervasive characteristic common to many methods for environmental decision-making is the inadequate inclusion of stakeholders in the decision-making process (Sharpe et al, 2021). This is also prevalent issue in spatial prioritization for restoration, as most published studies do not adequately include stakeholders (Castillo-Mandujano & Smith-Ramírez, 2022). While this problem could be solved by investing time and resources to ensure the participation of an inclusive and representative group of stakeholders, prioritization outcomes will only be valid for the specific context (e.g. geographical, ecological, economic, social, institutional) in which the decision-making process took place. Therefore, researchers could be tempted to reduce the participation of stakeholders in spatial prioritization methods to make the process simpler and with more generalizable outcomes, however decreasing the legitimacy of the results (Sharpe et al, 2021). This may be particularly true for spatial analyses, as the tasks of data collection, processing and analysis are intense in terms of time and computational resources.

The increasing availability of free spatial information, geospatial processing packages, and cloud computing capabilities have expanded the frontiers of what can be done in environmental spatial analysis (Kumar & Mutanga 2018; Tamiminia et al, 2020). These new tools may offer an opportunity to generate a new era for Multi-Criteria Spatial Decision Analysis, where researchers focus on developing on-line decision-making interactive platforms, and stakeholders operate them in real-time to evaluate different scenarios based on specific context. In this work, we present preliminary results of an ongoing project aimed on developing a free online interactive decision-making geospatial platform for guiding the selection of areas for ecological restoration in Chile. The prototype, called "RePlant alpha", uses R coding for requesting and managing the data, and for framing and running the decision-making algorithms, Google Earth Engine (GEE) for collecting and preprocessing satellite-based spatial data, and an online viewer for interactively showing the results.

2. RePlant alpha

The current prototype is a computer-based platform that integrates the flexibility of R coding with the cloud computing capabilities of Google Earth Engine (Fig. 1). In general terms, the platform works based on a set of predefined indicators (including the ecological, social and economic dimensions), which depending on their characteristics, are processed on GEE or in a local computer. Currently, all satellite-based indictors are cloud-computed in GEE, whereas the other indicators are computed from geospatial data stored in a local computer. Once all the indicators have been computed and standardized into compatible units, they are integrated through a Spatial Multi-Criteria Analysis

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(SMCA). During the integration process, a sensitivity analysis is performed to help defining the weights used in the SMCA. In addition, an optional routine is available to run all the possible combinations of weights as a pre-cached database of results or to build a metamodel. Results are then uploaded to a web-based mapping platform (ArcGis online) to produce interactive maps (Fig. 1).

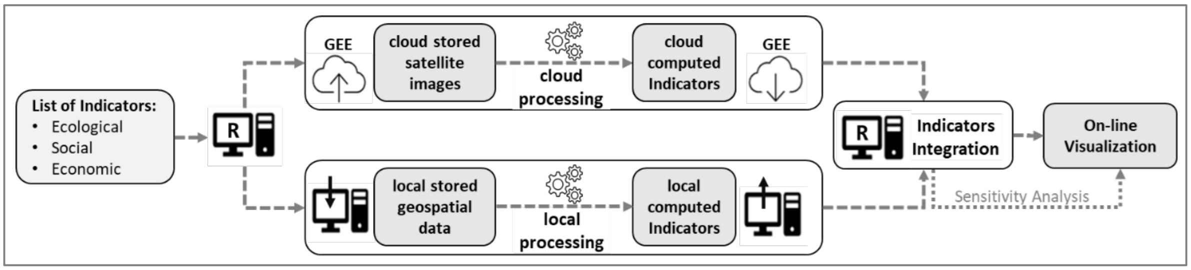

Figure 1. Diagram representing the main processes implicated in generating the prioritization of areas for restoration in the RePlant alpha platform.

3. RePlant in action

With the aim to show the potential of the current prototype, we used RePlant alpha to identify areas for restoration within the administrative region of Valparaíso, in Central Chile (Figure 2). This region of 16,396 km^2 has a Mediterranean climate, with annual rainfalls of 350mm concentrated predominantly during winter months. Original vegetation is mainly represented by schlerophyll forests and shrublands, which are currently relegated to higher and steeper areas, while lower and flat areas have been largely transformed for urbanization, agriculture and forestry. Changes in landscape composition and structure have made this region prone to forest fires, which has intensified the negative impacts of land transformation and degradation.

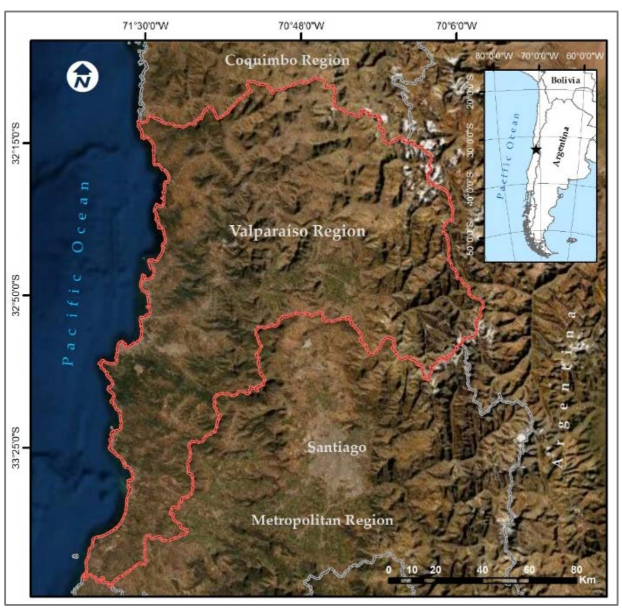

Figure 2. Map showing the area where the prioritization was performed. The Valparaiso Region is shown with a red border.

a. **Selection of indicators**

We selected six indicators to test the platform. We decided to use indicators that could be computed with freely accessible data but were at the same time useful to determine areas with restoration needs. To select these indicators, we considered not only factors involved in the potential success of restoration processes, but also those related to the social impact and operational feasibility of the implementation in the area (Fernandez et al. 2010, Fernández & Morales 2016). The indicators were divided into three main categories: ecological, social, and economic (Table 1). The selected indicators were: Normalized Difference Vegetation Index (NDVI), Difference Normalized Burn Ratio (dNBR), slope and potential erosion index, population density and distance to roads.

The NDVI and dNBR were chosen to assess vegetation changes (during the year) and detect burned area (December to March). We chose to use slope because steep areas should have priority over flat ones due to higher risk of future soil loss, landslides, and floods. Because not all the areas with high slopes have the same characteristics of erodibility and rainfall erosivity we added the potential erosion index to account for that variability in steep areas. Since local community support for any restoration project is important (Morales et al. 2020), population density could give an estimate of the potential community participation in any given area. Finally, the proximity to roads indicator was selected to give greater value to sites closer to roads, to prioritize areas that have fewer logistical limitations to carry supplies, both in terms of vegetative plant material and human resources.

Table 1. List of selected main indicators including classification and basic information

Indicator	Category	Description/Objective	Source	Scale
NDVI	Ecological	Calculation of NDVI over the last 5 years for each sample unit to evaluate the trajectory of vegetation in the sector	Landsat	30m/pixel
dNBR	Ecological	Calculation of dNBR based on the difference between pre- and post-fire seasons, to estimate damage severity	Landsat	30m/pixel
Slope	Ecological	Calculation of slope in percentage to estimate erosion potential	Digital Elevation Model / Aster	30m/pixel
Potential erosion index	Ecological	Estimation of potential erosion are based on an empirical qualitative model (IREPOT) and represent risk of erosion using specific characteristics of the studied areas.	Spatial data / IDE	1/50000
Population Density	Social	Estimation of population density to calculate the potential for community support	Spatialized census data / IDE	Census block
Proximity to roads	Economic	Generation of distance map to main and secondary roads to estimate ease of access to the area	Spatial data / IDE	1/10000

b. Indicator´s building process

i. **Cloud data processing**

The main objective of this proof of concept was to automatize the compilation and analysis of the information needed to build some of the indicators. GEE can be accessed through a web-based Integrated Development Environment (IDE) or by a Python Application Programming Interface (API). To integrate GEE to R we use the package “Reticulate” that provides an interoperability layer to use Python in a R session (Ushey et al 2022). In addition, the GEE Python API was installed using the package “rgee” (Aybar 2022). These two packages allowed us to connect to GEE with our credentials using Python in a R session.

A shapefile of the study area was uploaded to GEE to delimit the area of interest. Tier 1 Landsat 8 image collection was selected and later processed to eliminate unwanted pixels (e.g. clouds, shadows) using a mask based on the quality band (pixel_qa). The preprocessed images were used to calculate monthly NDVI and NBR during 2017. The monthly indexes were then compiled into one composite raster representing the median of 12 months for each index. Slope was derived from a Digital Elevation Model available in the GEE datasets (SRTM Plus). The resulting composites were cut to the extension of the study area and then exported as a raster to the local R session.

ii. **Local data processing**

The methodology described in this section uses the “sp” (Pebesma & Bivand 2005), “sf” (Pebesma, 2018), “stars” (Pebesma, 2021), “tidyr” (Wickham & Girlich 2022) and the “Raster” packages in R (Hijmans, 2022).

The data needed to build the rest of the indicators was not available in GEE. Therefore, they were built using a local working directory and produced using R GIS tools. Some indicators such as population density (PD), distance to roads (DR) and potential erosion index (PEI) were in a vectorial format; therefore, we transformed them to a raster format.

PD was derived from a comma delimited file that was then filtered leaving only the continental territory (i.e. removing outer islands) as part of the study. The resulting data was then spatialized assigning the proper data to each administrative municipality using the “stars” package (Pebesma, 2021) and transformed into a raster file. DR was derived from a vectorial layer that included all the road infrastructure of the study area. The vectorial layer was rasterized calculating the distance from cells that were not identified as populated areas to cells identified as roads, using the command distance from the package “raster” (Hijmans, 2022). PEI corresponded to the results delivered by a potential erosion risk index model (IREPOT; by the acronym in Spanish) (CIREN 2010). The model also integrates different variables including topographic-hydrological, rainfall aggressiveness, soil and vegetation. All the variables were later integrated into a single qualitative index which was represented by four qualitative categories of potential risk (none or low, moderate, severe and very severe). Each category was associated to a risk class ranging from 1 to 4 (low to very severe). This final layer was rasterized using the risk class.

c. Integration of indicators

All generated raster layers were checked and reprojected and resampled if needed. The new raster layers were then normalized so that they were in the same range of values between 0 and 1. This was done using the min-max rescaling method. Once all the layers were in the same numerical scale, they were integrated in a SMCA using different weights. Because the use of weights can be subjective, we included a sensitivity analysis. This analysis can give the user some insight regarding the influence of each weight on the final SMCA results. Weight values were changed one at a time by ± 0.2 starting from 0 to ± 1. For each change in weight a raster was built that was later compared to a reference raster map representing a full model including all the indicators without weights. To represent all the comparisons, a contingency table showing the agreement (%) for each indicator was made to summarize the results using the package "diffeR" (Gilmore & Santacruz 2019) (Table 2).

Following the results from the sensitivity analysis, the weights for each indicator were defined according to their effect on the model. For example, for indicators that had a low impact (e.g. population density) a low weight values were assigned (0.1). In contrast, for indicators with a high impact on the outcome (e.g. proximity to roads) and slope, low weight values were assigned., The rest of the indicators were set to 0.2. The priorization raster or priority index from the SMCA was reclassified in quartiles for ease of interpretation and vectorized to make it compatible with a vectorial territorial administrative layer.

d. Cache of different weights combinations

The code includes an option were the SMCA results for each possible combinations of weights can be cached in the computer, cloud, or server. However, we do not recommend its use because the number of weights' combinations is really high (approximately 44 million different combinations for 7 indicators). In our case the resulting rasters from each weight combination had a size of 7 MB, which multiplied by the number of different weights combinations, would require 308 TB of storage.

e. Visualization platform

The vectorial layers representing the priorization and the territorial administrative divisions were manually uploaded to a web-based mapping software (Arcgis online®, ESRI). The platform has three interactive layers that the user can explore. A main layer representing the areas with a high priorization index (>0.6) called *priority areas*; a secondary layer showing the total priority area per municipality called *priority rate per municipality* (%); and a third layer that corresponds to the reclassified priorization index. Each layer has a caption with their respective index or percentage value (Figure 3).

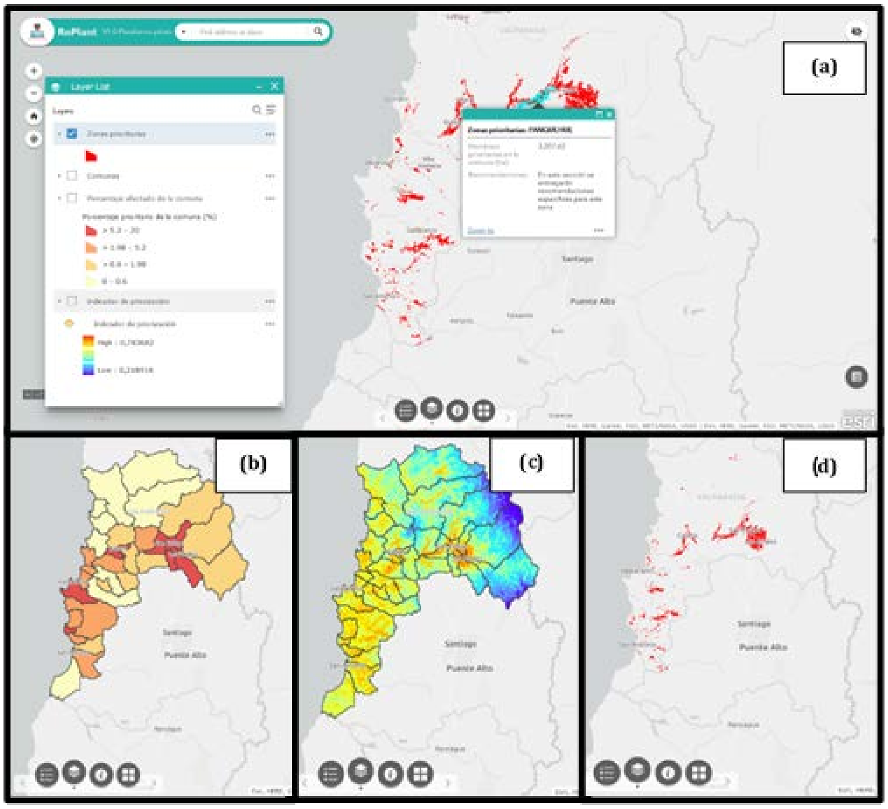

Figure 3. General view of the"Replant alpha" platform and the priorization results presented in the ArcGIS web map. (a) The platform where the results to be displayed can be manipulated, (b) Priority percentage of the municipality (%), (c) Prioritization indicator (0 to1) and (d) Priority restoration zones representing areas with high restoration priority.

4. Results

a. SMCA output

The prioritized areas corresponded to 18% of the total area of the Valparaiso region (160,6977 ha, not including insular areas). The provinces with higher level of degradation were Valparaiso and San Antonio with a 5.5 and 4% of the total region area respectively (Appendix A1). Coincidently, the top three municipalities with the highest degraded area were located in these provinces. Valparaiso province has two municipalities, Casablanca (2.9%) and Valparaiso (1.1%), with the highest values of degradation. San Antonio province had one municipality (San Antonio) with 1.3 % of the total area of region in needs of restoration. The rest of municipalities of the region had less than 1% of the total area of the region classified as in need of restoration (Appendix A1). It is important to note that even though the proportional contribution of the different municipalities to the total could be seen as small in comparison with the total area of the region, some municipalities have more than 40% of the area to restore per province. All 35 municipalities are in need of restoration although their contribution to each degraded province can vary from 2.3 to 53.1%.

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b. Processing times

The whole script for seven indicators takes approximately 40 minutes (not including permutations of the different weights or cache of different combinations), on a top-of-the-line computer. However, it is important to consider that running the whole script will not be always necessary, as many of the processed indicators could be stored as cached data; thus, requiring to run the whole script once a year or when updated information is available (e.g. new satellites images, updated social data). In any case, if more processing power is needed, it can be scaled to a virtual machine on any cloud service without issue.

c. Sensitivity analysis

The sensitivity analysis showed that population density is the less sensitive indicator, meaning that changes in the weight associated to this indicator have a minimal impact on the prioritization model. In contrast, the most sensitive indicators, proximity to roads and slope, when not considered in the priorization model (weight equal to zero), had significant impacts on the model with only a 12% and 25% agreement, respectively. In any case, most of the indicators were quite robust to weight changes (0.8 points reduction) (Table 2).

Table 2. Agreement (%) results for changes in weights of each indicator (ranging from -1 to 1). The analysis corresponds to a comparison from a raster representing a weight change for a specific indicator and the raster representing the baseline model.

	Weights										
Indicators	-1	-0.8	-0.6	-0.4	-0.2	0	0.2	0.4	0.6	0.8	1
Population Density	98	98	98	99	99	99	99	100	100	100	100
EJH	4	9	16	25	34	45	57	66	75	86	100
Erosion	40	41	43	46	53	62	72	79	84	90	100
NBR	16	26	36	88	45	54	63	70	79	88	100
NDVI	0	2	7	17	30	42	53	63	73	85	100
Proximity to roads	2	2	3	3	4	12	32	50	66	80	100
Slope	0	1	4	10	17	25	40	55	68	82	100

5. Future improvements

a. Code and indicators

The code was written with only for seven indicators, as this was a proof of concept. Including more indicators can vary from a straightforward process to requiring major coding. To avoid this issue, all the code that includes absolute paths and filenames must be changed to relative paths. This change will simplify the directory structure necessary for the different data files and will allow the code to run in any device or cloud setup. Relative indicator names are needed to make the code shorter and faster, especially for functions in a loop and processor intensive tasks. Finally, these changes will help the future platform administrator make changes or updates easily. While the current priorization module has only seven basic indicators, a newer version of the platform is been developed to add 11 new indicators to the SMCA (Table 3). Future versions of the platform will allow the users to select the indicators and the weights used in the SMCA that are more appropriate to their needs.

b. Data visualization

In terms of the data visualization, currently the results are not transferred automatically. The approach to use will depend on who will host the final version of the platform. There are three options on how to transfer the data to a visualization module. One option is to build a tailored platform and graphic interface using a hybrid composition of web development, databases, and cloud computing. For example, a web service using HTML5, CSS3, Javascript, JQuery and Python3 technologies, through the Django Framework, for the presentation layer (frontend) and the processing layer (backend) would work well. For data storage and query response, a MySQL database can be used, while the complete solution could be built on a cloud service such as Google Cloud or Amazon Web Services (AWS), including Google Compute Engine (GCE) instances and Cloud SQL services. This solution is more cost-effective because the only fixed cost in the long term would be the use of the cloud services. Another option is to keep using the ArcGis web-based mapping solution (ArcGis online ®) together with R-ArcGIS Bridge and ESRI's Web AppBuilder framework to provide a web-based frontend. A similar solution would be the use of RStudio and packages of different cloud services such as Shiny, Shinyapps or RStudio Connect. Although these are the best solutions in terms of integration, they require a subscription to the services and the costs can escalate quickly depending on the services demanded by users and number of users connected.

c. Recommendations for restoration activities, costs and funding

Future versions of the platform will include specific information for selected areas according to the vegetation communities that were originally present. The prototype presented here incorporates a generic text that is displayed when the mouse cursor is placed on the prioritized areas. To include restoration recommendations for each vegetation community, information needs to be compiled from diverse sources, including non-peer-reviewed publications such as technical documents, books, as well as scientific articles. Some of this information is already available for Chile in Fernández et al. (2010) but it needs to be updated and provided in more detail. Once this information is ready, estimative costs per hectare can be added for some of the activities. Finally, general information on funding opportunities to finance these activities will be also added.

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Table 3. General information about the indicators that a future version of the platform will include

Indicador	Category	Focus	Description/ Indicator objective	Data source	Data source scale
NDVI temporal changes	Ecological	Land degradation	NDVI was calculated using the last 5 years for each sample unit to evaluate the trajectory of vegetation in the sector	Landsat	30m/pixel
dNBR	Ecological	Land degradation	Calculated using the difference between pre- and post-fire seasons, to estimate damage severity	Landsat	30m/pixel
Land use	Ecological	Land degradation	Classification of land uses (e.g. urban, agricultural, forestry, natural) according to their potential for restoration	National Native Forest Inventory	1/5000
Slope	Ecological	Abiotic factors (erosion proxy)	Calculation of slope in percentage to estimate erosion potential	Aster Digital elevation model	30m/pixel
Aspect	Ecological	Abiotic Factors (HR and T° proxy)	Calculation of exposure in degrees to estimate potential soil moisture/temperature conditions.	Aster Digital elevation model	30m/pixel
Proximity to Priority Conservation Sites	Ecological	Landscape Continuity	Generation of a map including proximity to a priority site and/or areas part of priority sites to prioritize landscape continuity	Chilean Geospatial Data Infrastructure	1/10000
Proximity to SNASPE	Ecological	Landscape Continuity	Creation of a map of belonging and proximity to priority protected areas of the State to prioritize landscape continuity	Chilean Geospatial Data Infrastructure	1/10000
Proximity to a native vegetation fragment	Ecological	Landscape Continuity	Map representing the distance to native vegetation patches to prioritize landscape continuity	National Native Forest Inventory	1/5000
Vegetation cover type	Ecological	Landscape Diversity	Vegetation cover map categorized by functional types (herbaceous, evergreen,	Landsat	30m/pixel

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Indicador	Category	Focus	Description/ Indicator objective	Data source	Data source scale
			deciduous), to prioritize functional groups to be reforested		
Particulate Matter	Social/Economic	Social Impact	Urban particulate matter maps for 2.5- and 10-micron, o establish priority zones for restoration	National Air Quality Information System and proprietary network of contamination monitor (Fernández IC)	1/10000
Land tenure	Social/Economic	Social Impact	Map of properties and/or land ownership to evaluate accessibility to areas with restoration priority	Chilean Natural Resources Information Center	100m/pixel
Multidimensional Poverty	Social	Social Impact	District map of multidimensional poverty to prioritize by level of socioeconomic vulnerability	National Socioeconomic Characterization Survey	Census block
Extreme Poverty by Income	Social	Social Impact	District map of extreme poverty to prioritize by level of socioeconomic vulnerability	National Socioeconomic Characterization Survey	Commune
Unemployment Rate	Social	Social Impact	District unemployment map to estimate the need for jobs in affected areas	National Socioeconomic Characterization Survey	Commune
Percentage of population with Higher Education	Economic	Human Capital	District unemployment map to estimate the need for jobs in affected areas	National Socioeconomic Characterization Survey	Commune
Distance from population centers	Economic	Logistic	Map representing the distance to population centers to estimate the ease of obtaining inputs	Chilean Geospatial Data Infrastructure	Commune
Population Density	Economic	Logistic	Estimation of population density to estimate the potential to recruit local labor	Chilean Geospatial Data Infrastructure	Commune

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Indicador	Category	Focus	Description/ Indicator objective	Data source	Data source scale
Proximity to roads	Economic	Logistic	Map of distances to main and secondary roads to estimate ease of access to the area	Chilean Geospatial Data Infrastructure	1/10000

6. Conclusions

This exercise shows that developing a platform to assess restoration priorities required not only expertise in remote sensing and GIS but also in ecological modeling and concepts and approaches from landscape ecology and ecological restoration. To integrate these different disciplines, you must develop multi-scale indicators. These indicators need to faithfully represent landscape degradation at multiple geographic scales and inter-annual time periods, incorporating the relationship between degradation and the socio-economic situation in the study area. Likewise, the techniques applied need to allow the handling and analysis of a large amounts of data in an autonomous manner with a high demand for computational processing. In spite of the multifaceted computational processing involved, the platform requires to deliver the results of these complex analyses results in simple to interpret results with practical recommendations for restoration.

Currently, there are different software tools (e.g. Zonation, Marxan) that are capable of performing spatial prioritization to select sites and identify actions to develop management and/or conservation plans in areas of interest. However, these tools require downloading a computer program, collecting and generating all the required geospatial information, training in the use of the software, and running the program on computers with sufficient computing power to handle multiple layers. These requirements limit the use of these tools, especially in those cases where a large part of the necessary geospatial information needs to be collected, and even more so when the complexity of the problem and geographic extension of the territories under analysis require intensive use of human and monetary resources and technical capabilities to implement the prioritization. In contrast, the solution proposed in this project will have all this geospatial information already loaded into the system, eliminating the requirement for users to make the effort to collect and generate the required indicators themselves. In addition, users will access the system through an intuitive and user-friendly graphical interface, which will be designed to minimize the need for GIS knowledge, thus maximizing the potential of the tool to be used by a wide and diverse target audience.

Another relevant point is that the proposed solution works based on free and open access geospatial information and the data processing will be done through the "Google Earth Engine" system, which also corresponds to a free and open access system, and therefore the development of solutions does not require the use of technologies that are protected by patents. Furthermore, the platform does not require a specific cloud computing service, and is able to use any solution available in the market (e.g. Google Cloud Services, Amazon Web Services or Microsoft Azure).

Improved versions of RePlant will undoubtedly contribute to improve the experience, transparency, and efficiency in decision making to prioritize the restoration of degraded ecosystems. In addition, the fact that it is an interactive platform where users can modify the relative importance of different indicators and dimensions will facilitate the dialogue between decision-makers who may have conflicting opinions. In conjunction with these advantages, RePLant can become a tool for scenario generation and discussion, as well as a base platform for developing other spatial prioritization objectives. In addition, this tool can contribute to decision-making of public policy instruments such as National Strategy for Climate Change and Vegetation Resources, National Landscape Restoration Plans, among others. At an international level, this type of tool can help in the accomplish targets and goals of commitments assumed by the countries for the restoration of degraded ecosystems such as the Bonn Challenge, 20x20 Initiative, and the National Determined Contribution (NDC).

7. Funding Information

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8. Author contributions

Conceptualization, Narkis S. Morales and Ignacio C. Fernández; Scripting and coding, Narkis S. Morales; Analysis, Narkis S. Morales, Writing original draft, Narkis S. Morales, Ignacio C. Fernández, Leonardo P. Durán and Waldo A. Pérez; Writing – review & editing, Narkis S. Morales, Ignacio C. Fernández and Leonardo P. Durán; Figures, Narkis S. Morales, Ignacio C. Fernández and Waldo A. Pérez.

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10. Conflict of Interest

The authors declare no conflict of interest

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11. Appendix A

Table A1. Prioritized area per administrative units in hectares, percentage of total prioritized area and percentage of commune area deemed of restoration efforts

Province	Commune	Area (ha)	Area (%)	% of total area
Los Andes (1%)	Calle larga	4758	28,9	0.3
	Los andes	2684	16,3	0.2
	Rinconada	3096	18,8	0.2
	San esteban	5946	36,1	0.4
	Subtotal	**16484**		
Marga Marga (1,8%)	Limache	10466	35,3	0.6
	Olmué	2559	8,6	0.2
	Quilpué	12395	41,8	0.8
	Villa Alemana	4241	14,3	0.3
	Subtotal	**29661**		
Petorca (2,2%)	Cabildo	6921	19,4	0.4
	La Ligua	11049	30,9	0.7
	Papudo	3600	10,1	0.2
	Petorca	7666	21,5	0.5
	Zapallar	6473	18,1	0.4
	Subtotal	**35709**		
Quillota (1,6%)	Calera	1790	7,1	0.1
	Hijuelas	3275	13,0	0.2
	La Cruz	3171	12,6	0.2
	Nogales	6572	26,1	0.4
	Quillota	10403	41,3	0.6
	Subtotal	**25211**		
San Antonio (4%)	Algarrobo	13900	21,6	0.9
	Cartagena	10139	15,7	0.6
	El quisco	3075	4,8	0.2
	El tabo	7834	12,1	0.5
	San Antonio	21297	33,0	1.3
	Santo Domingo	8239	12,8	0.5
	Subtotal	**64484**		
San Felipe de Aconcagua (2,5%)	Catemu	5738	14,4	0.4
	Llaillay	5720	14,3	0.4
	Panquehue	4996	12,5	0.3
	Putaendo	8237	20,7	0.5
	San Felipe	9270	23,2	0.6
	Santa María	5920	14,8	0.4
	Subtotal	**39881**		
Valparaíso (5,5 %)	Casablanca	47015	53,1	2.9
	Concón	2006	2,3	0.1

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Puchuncaví	6503	7,3	0.4
quintero	10704	12,1	0.7
Valparaíso	17452	19,7	1.1
Viña del mar	4875	5,5	0.3
Subtotal	**88555**		
Total	**299985**		

12. References

Abhilash, P.C. Restoring the Unrestored: Strategies for Restoring Global Land during the UN Decade on Ecosystem Restoration (UN-DER). Land 2021, 10, 201, doi:10.3390/land10020201.

Aronson, J.; Goodwin, N.; Orlando, L.; Eisenberg, C.; Cross, A.T. A World of Possibilities: Six Restoration Strategies to Support the United Nation's Decade on Ecosystem Restoration. Restoration Ecology 2020, 28, 730–736, doi:10.1111/rec.13170.

Aybar, C. Rgee: R Bindings for Calling the "Earth Engine" API; 2022.

Brancalion, P.H.S.; Niamir, A.; Broadbent, E.; Crouzeilles, R.; Barros, F.S.M.; Almeyda Zambrano, A.M.; Baccini, A.; Aronson, J.; Goetz, S.; Reid, J.L.; et al. Global Restoration Opportunities in Tropical Rainforest Landscapes. Science Advances 2019, 5, eaav3223, doi:10.1126/sciadv.aav3223.

Castillo-Mandujano, J.; Smith-Ramírez, C. The Need for Holistic Approach in the Identification of Priority Areas to Restore: A Review. Restoration Ecology 2022, e13637, doi:10.1111/rec.13637.

CIREN, (Centro de Información de Recursos Naturales); Flores, J.P.; Martínez, E.; Espinosa, M.; Avendaño, P.; Ahumada, I.; Torres, P.; Henríquez, G. Determinación de la erosión actual y potencial de los suelos de Chile: Región de Valparaíso. Síntesis de resultados. (Pub. CIREN N°145). 2010

Fernández, I.; Morales, N.; Olivares, L.; Salvatierra, J.; Gómez, M.; Montenegro, G. Restauración Ecológica Para Ecosistemas Vegetales Nativos Afectados Por Incendios Forestales; LOM: Santiago, Chile, 2010.

Fernandez, I.C.; Morales, N.S. A Spatial Multicriteria Decision Analysis for Selecting Priority Sites for Plant Species Restoration: A Case Study from the Chilean Biodiversity Hotspot. Restoration Ecology 2016, 24, 599–608, doi:10.1111/rec.12354.

Fernández, I.C.; Morales, N.S. A Spatial Multicriteria Decision Analysis for Selecting Priority Sites for Plant Species Restoration: A Case Study from the Chilean Biodiversity Hotspot. Restoration Ecology 2016, 24, 599–608, doi:10.1111/rec.12354.

Gilmore, R.; Santacruz, A. DiffeR: Metrics of Difference for Comparing Pairs of Maps or Pairs of Variables; 2019.

Hijmans, R.J.; van Etten, J. Raster: Geographic Analysis and Modeling with Raster Data; 2012.

Huang, I.B.; Keisler, J.; Linkov, I. Multi-Criteria Decision Analysis in Environmental Sciences: Ten Years of Applications and Trends. Science of The Total Environment 2011, 409, 3578–3594, doi:10.1016/j.scitotenv.2011.06.022.

Kumar, L.; Mutanga, O. Google Earth Engine Applications Since Inception: Usage, Trends, and Potential. Remote Sensing 2018, 10, 1509, doi:10.3390/rs10101509.

Malczewski, J. GIS - based Multicriteria Decision Analysis: A Survey of the Literature. International Journal of Geographical Information Science 2006, 20, 703 - 726, doi:10.1080/13658810600661508.

Mendoza, G.A.; Martins, H. Multi-Criteria Decision Analysis in Natural Resource Management: A Critical Review of Methods and New Modelling Paradigms. Forest Ecology and Management 2006, 230, 1–22, doi:10.1016/j.foreco.2006.03.023.

Morales, N.S.; Fernández, I.C.; Duran, L.P.; Venegas-González, A. Community driven Post-Fire Restoration Initiatives in Central Chile: When Good Intentions Are Not Enough. Restoration Ecology 2021, 29, e13389, doi:10.1111/rec.13389.

Orsi, F.; Geneletti, D. Identifying Priority Areas for Forest Landscape Restoration in Chiapas (Mexico): An Operational Approach Combining Ecological and Socioeconomic Criteria. Landscape and Urban Planning 2010, 94, 20–30, doi:10.1016/j.landurbplan.2009.07.014.

Pebesma, E. Simple Features for R: Standardized Support for Spatial Vector Data. The R Journal 2018, 10, 439–446, doi:10.32614/RJ-2018-009.

Pebesma, E. Stars: Spatiotemporal Arrays, Raster and Vector Data Cubes; 2022.

Pebesma, E.J.; Bivand, R.S. Classes and Methods for Spatial Data in R. R News 2005, 5, 9–13.

Sharpe, L.M.; Harwell, M.C.; Jackson, C.A. Integrated Stakeholder Prioritization Criteria for Environmental Management. Journal of Environmental Management 2021, 282, 111719, doi:10.1016/j.jenvman.2020.111719.

Steffen, W.; Richardson, K.; Rockström, J.; Cornell, S.E.; Fetzer, I.; Bennett, E.M.; Biggs, R.; Carpenter, S.R.; de Vries, W.; de Wit, C.A.; et al. Planetary Boundaries: Guiding Human Development on a Changing Planet. Science 2015, 347, 1259855, doi:10.1126/science.1259855.

Strassburg, B.B.N.; Iribarrem, A.; Beyer, H.L.; Cordeiro, C.L.; Crouzeilles, R.; Jakovac, C.C.; Braga Junqueira, A.; Lacerda, E.; Latawiec, A.E.; Balmford, A.; et al. Global Priority Areas for Ecosystem Restoration. Nature 2020, 586, 724–729, doi:10.1038/s41586-020-2784-9.

Tamiminia, H.; Salehi, B.; Mahdianpari, M.; Quackenbush, L.; Adeli, S.; Brisco, B. Google Earth Engine for Geo-Big Data Applications: A Meta-Analysis and Systematic Review. ISPRS Journal of Photogrammetry and Remote Sensing 2020, 164, 152–170, doi:10.1016/j.isprsjprs.2020.04.001.

Ushey, K.; Allaire, J.J.; Tang, Y. Reticulate: Interface to "Python"; 2022.

Vettorazzi, C.A.; Valente, R.A. Priority Areas for Forest Restoration Aiming at the Conservation of Water Resources. Ecological Engineering 2016, 94, 255–267, doi:10.1016/j.ecoleng.2016.05.069.

Wickham, H.; Girlich, M. Tidyr: Tidy Messy Data; 2022.