

A spatial simulation framework for afforestation policy assessment in Chile: accounting for uncertainty in projected land-use change and hydrological risk

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Abstract

Context. Large-scale afforestation programs are climate-mitigation commitments and spatial land-use interventions requiring feasibility and environmental risk assessment, especially in heterogeneous, water-constrained landscapes. Land-use simulations rarely account for spatial uncertainty, limiting evaluation of whether targets remain achievable under different certainty levels.

Objectives. This study aims to develop a spatial simulation framework to assess the feasibility, distribution, configuration, and uncertainty of afforestation targets under contrasting policy scenarios. It also examines how projected afforestation affects exposure to water-stressed catchments.

Methods. We developed a spatial simulation framework based on the Future Land Use Simulation (FLUS) model, integrating FT-Transformer suitability estimation, land-use allocation, ensemble uncertainty mapping, and catchment-level water-stress screening. The framework was applied to two policy scenarios in central-southern Chile: a trend scenario and an incentive scenario promoting native forest afforestation. For each scenario, 100 simulations assessed the distribution, configuration, and certainty of projected changes.

Results. The suitability model improved classification accuracy from 0.720 to 0.772 compared with the standard FLUS ANN module. Both scenarios fell short of the target by 25.3%-31.5%, although it represents only 5.5% of the available area. Incentives increased afforested area by 8.9%, producing fewer, larger, and more connected patches. However, incentives shifted expansion toward more hydrologically sensitive catchments. Only 15.8% and 27.2% of simulated patches were highly certain in the trend and incentive scenarios, respectively.

Conclusions. Our results highlight the importance of considering spatial feasibility, landscape configuration, uncertainty, and hydrological trade-offs in afforestation planning, rather than focusing exclusively on gross committed area. Thus, our framework enables a robust and spatially explicit evaluation of afforestation policies in Chile and other heterogeneous landscapes.

1. Introduction

Large-scale afforestation programs are not only climate mitigation commitments but also spatially explicit land-use interventions that require prior feasibility and environmental risk assessment. As countries increasingly adopt afforestation to enhance carbon sequestration (Chang et al. 2017; Bryan et al. 2018; Bastin et al. 2019), these interventions often target heterogeneous landscapes where biophysical, socioeconomic, and neighborhood interactions shape land-use dynamics in nonlinear and stochastic ways (Verburg et al. 2019; García-Álvarez et al. 2022). This complexity introduces substantial uncertainty in both the trajectories and spatial distribution of land-use change.

Beyond carbon benefits, afforestation can generate important environmental trade-offs. While it may support biodiversity conservation and ecosystem services, it can also alter hydrological regimes, fire

dynamics, and ecosystem functioning depending on location and context (Farley et al. 2005; Veldman et al. 2019; Gómez-González et al. 2024). These effects depend not only on the total area afforested, but also on the spatial configuration and environmental setting of new forests, making spatially explicit assessment essential for policy design.

Land-use change models are widely used to explore future landscape trajectories and inform decision-making (Bürgi et al. 2017; Verburg et al. 2019). Among these, the Future Land Use Simulation (FLUS) model provides an effective framework to represent land-use dynamics under competition, neighborhood effects, and historical inertia (Liu et al. 2017; Chen et al. 2022). FLUS combines a suitability module, typically based on artificial neural networks (ANNs), with a cellular automaton (CA) allocation process. However, the standard ANN-based suitability component may be less effective in capturing complex nonlinear interactions among predictors compared to recent deep learning approaches designed for tabular data (Gorishniy et al. 2023a). In addition, most applications do not assess the robustness of projected spatial patterns across repeated simulations, despite the stochastic nature of land-use allocation and the multiple sources of uncertainty involved.

A key limitation therefore lies in how these models are used for policy analysis. Although allocation in models such as FLUS is inherently stochastic, results are often derived from single simulation runs and interpreted as deterministic projections. This practice overlooks the variability of possible spatial outcomes and may bias the evaluation of policy feasibility, particularly when less probable but policy-relevant outcomes are not considered.

In this context, Chile provides a policy-relevant case study. The country has committed to carbon neutrality by 2050 and to afforesting 200,000 ha by 2030, prioritizing native forests due to their broader ecological benefits (Ministerio de Medio Ambiente (MMA) 2021; Gómez-González et al. 2024). However, the spatial feasibility of this target remains uncertain in a landscape characterized by high heterogeneity, competing land uses, and increasing water constraints (Heilmayr et al. 2016; Herrera-Benavides et al. 2024). This makes Chile a relevant case not only for assessing afforestation feasibility, but also for examining how uncertainty in spatial projections affects the evaluation of policy targets.

Water availability is a particularly critical constraint. Central Chile has experienced increasing water stress, with several catchments reaching high or extreme levels in recent decades (Boisier et al. 2024). Afforestation can further alter catchment water balances through increased evapotranspiration, especially in water-limited environments (Farley et al. 2005; Baldocchi and Penuelas 2019). As a result, afforestation policies that are beneficial from a carbon perspective may entail significant hydrological trade-offs depending on where expansion occurs.

To address these challenges, we develop a spatial simulation framework that integrates FT-Transformer-based suitability estimation with the FLUS allocation model and an ensemble approach to explicitly characterize uncertainty in projected land-use change. The framework also incorporates catchment-level water-stress indicators to assess potential hydrological trade-offs.

Specifically, we address three questions: (i) whether the national afforestation target can be achieved under biophysical and legal constraints; (ii) how policy incentives affect the spatial distribution and configuration of afforestation; and (iii) how these changes influence exposure to water-stressed catchments under uncertainty. By combining suitability modeling, stochastic simulation, and ensemble-based analysis, this study provides a more robust and spatially explicit basis for evaluating afforestation policies in heterogeneous and water-constrained landscapes.

2. Study area

The study area spans central-southern continental Chile (33.8°S–41.5°S; 70.2°W–73.5°W), from the O'Higgins Region to Los Lagos (Fig. 1). This territory is central to Chile's afforestation policy because of its landscape heterogeneity, long history of forest production, and the availability of land potentially suitable for establishing native forests; it also lies within a global biodiversity hotspot (Myers et al. 2000). The area shows a marked climatic transition, from Mediterranean conditions in the north (dry summers) to temperate-oceanic conditions toward the south, with orographic controls from the Coastal and Andes ranges shaping precipitation patterns.

Land cover is dominated by native forest (30.9%), shrubland (19.4%), exotic forest plantations (10.2%), and a combined grassland/cropland share of 19.1%; bare areas are ~ 10.1%. Under Chilean legislation, native forest is classified into forest types (e.g., sclerophyllous, evergreen, and Nothofagus-dominated formations; Decree Law 701; Supreme Decree 259). The study area concentrates several forest types with relatively high sequestration rates used in the national inventory (4.3–6.6 t ha⁻¹ yr⁻¹), including Roble-Raulí-Coigüe, Evergreen, Lenga, and Coigüe-Raulí-Tepa.

The recent megadrought (2010–2022) pushed several basins into high to extreme water stress (WSI > 40% and > 70%), and multiple basins already show over-allocation of water-use rights, with projections showing further increases under a drying climate. These characteristics make the study area well suited to evaluate where carbon-driven afforestation may concentrate and how it may intersect with water-stress constraints.

3. Materials and Methods

We combined land-use suitability estimation and spatial allocation within a modeling framework to assess afforestation feasibility, spatial distribution, uncertainty, and hydrological risk under two afforestation scenarios. The framework uses the GeoSOS-FLUS CA allocation module, which requires two main inputs: estimates of class-specific suitability and the afforestable area available for simulation (See Fig. 2). Accordingly, Section 3.1 describes the spatial data and preprocessing used as input to assess suitability and to identify areas potentially available for afforestation. Section 3.2 presents the GeoSOS-FLUS allocation framework, the FT-Transformer-based suitability estimation, and how they are integrated for spatial prediction. Section 3.3 defines the afforestation scenarios, and Section 3.4 describes the spatial and uncertainty analyses used to compare the results of the scenarios.

3.1. Materials and preprocessing data.

Dynamic Land Cover for 2013–2018 (Galleguillos et al. 2024) was used as the baseline land-cover reference for simulating future land uses and estimating land-use occurrence probabilities. This 30-m product was derived from supervised Random Forest classifications using Landsat surface reflectance, SRTM topography, and auxiliary cartographic data, followed by trajectory-consistent temporal corrections. The 2013–2018 period is characterized by relative legal stability in environmental and land-use policies. The Dynamic land cover for 1990–2018 was also used to derive historical land-use changes predictors, including the frequency with which pixels were classified as native forest or forest plantation over the historical period. Land-cover classes were reclassified into classes of interest following the classification used by the Chilean forestry agency (CONAF) and resampled to a 1-ha resolution, consistent with the scale at which public/legal management is typically implemented (Supplementary material: Appendix A1).

Additionally, we used spatial variables based on distances and data from remote sensors as predictors to calculate suitability for conversion, as detailed in Appendix A3, Table A3. Catchments were classified by water stress using the Water Scarcity Index (WSI; Boisier et al. 2024) calculated for a long-term reference period (1960s-2010s) and an extreme megadrought-focused period (2010s), and scenario outcomes were evaluated across WSI classes.

3.2. Spatial simulation: Suitability estimation and FLUS allocation

GeoSOS-FLUS simulates land-use change by integrating an ANN-based suitability estimation with a bottom-up CA allocation process (Liu et al. 2017). The approach consists of two coupled components: (i) estimation of the probability of occurrence (suitability) for each land-use class, and (ii) CA allocation that combines suitability with neighborhood effects, inertia, and conversion costs to generate land-cover transitions (See Fig. 2). However, the standard FLUS suitability component relies on a conventional feed-forward ANN, may be less effective in capturing complex nonlinear interactions among predictors compared to recent deep learning approaches designed for tabular data (Gorishniy et al. 2023b). Therefore, we replaced the ANN suitability module with an FT-Transformer and used the conventional CA module from FLUS. Historical land cover data and legal restrictions are used to define the model's hyperparameters (weighting factor, self-adaptive inertia, and conversion costs). The proposed framework extends conventional FLUS applications in three ways: (i) replacing the standard ANN suitability module with a Transformer-based architecture better suited for tabular geospatial predictors; (ii) explicitly propagating stochastic allocation uncertainty through ensemble simulations; and (iii) linking spatial outputs with hydrological risk indicators at the catchment scale. For more details, see Appendix A2 of the supplementary material and the work of Liu et al. (2017).

3.2.1. Probability of occurrence (Suitability)

To estimate the probability of occurrence of each land-use class at each pixel, we use an NN based on the FT-Transformer architecture (Gorishniy et al. 2023b), a Transformer adaptation designed for tabular data (Vaswani et al. 2017). FT-Transformer has shown robust performance on tabular prediction tasks, comparable to typical machine-learning approaches, while remaining computationally efficient among pre-trained tabular architectures (Gorishniy et al. 2023a, b; Praven et al. 2024). A random training sample of 150,000 observations per class was obtained, and geospatial predictors were extracted for each sample (Appendix Table A3). In addition, we compared this suitability map with the standard ANN architecture available in the GeoSOS-FLUS model to determine whether using FT-Transformers is best.

3.2.2. CA allocation and transition rules

At each iteration, the CA allocates land-use classes based on combined transition probabilities that integrate suitability and spatial interaction terms (Liu et al. 2017) according to the following equation:

$$TP_{p,k}^t = P_{p,k} \times \Omega_{p,k}^t \times Inertia_k^t \times (1 - s_{c \rightarrow k})$$

Equation 2: combined probabilities.

Where $TP_{p,k}^t$ denotes the probability that pixel p transitions from its current class c to target class k at iteration t ; $P_{p,k}$ is the ANN-based suitability for class k ; $\Omega_{p,k}^t$ is the neighborhood effect; $Inertia_k^t$ is the inertia coefficient for class k ; and $s_{c \rightarrow k}$ is the conversion cost from class c to class k .

Class allocation is implemented using a stochastic roulette-wheel selection mechanism (Equation A2 in the Appendix), which introduces inherent variability even under identical settings. This stochasticity is integrated through the ensemble design described in Section 3.4.

3.3. Scenario design and land availability for simulation

We evaluate two scenarios: (i) a baseline scenario reflecting current dynamics of change, and (ii) an incentive scenario representing an afforestation incentive that prioritizes higher-sequestration forest types. The national commitment of 200,000 ha by 2030 is treated as a feasibility test under biophysical/legal constraints and land-use competition. Accordingly, we prescribe 2030 demand as the 2018 native-forest area plus 200,000 ha, while other land uses decrease proportionally to their baseline shares (details in Appendix A4). We assume that all afforestation (up to 200,000 ha) is implemented with native species in both scenarios, consistent with current legal limitations on afforestation with exotic species under Chilean law (Ministerio de Medio Ambiente 2022).

In the incentive scenario, we add a predictor representing incentive value to the FT-Transformers so that suitability reflects the policy preference. This predictor is constructed by: selecting areas with a strong historical native forest signal (e.g., > 80% native forest frequency in Dynamic LandCover), identifying potential areas for each type of forest using vegetation belts (Luebert and Pliscoff 2017) and assigning incentive levels proportional to the sequestration rates used in the official Chilean greenhouse gas

inventory (Ministry of the Environment 2024). The detailed construction and weighting scheme (including the conceptual weighting equation and discretization) is provided in Appendix A5.

These two contrasting scenarios were defined not only to compare projected afforestation under current trends and under policy intervention, but also to assess the framework's ability to provide a robust and spatially explicit assessment of the effects of policies—whether in terms of extent and spatial distribution, their certainty, landscape configuration, or potential increases in hydrological risk.

To define potentially eligible afforestation areas, we applied spatial filters reflecting legal restrictions, policy definitions, economic suitability, and biophysical limits. Briefly, we (i) applied the legal definition of forestation (Decree Law No. 701, 1974), (ii) restricted candidate soils to those considered suitable for forestry or conservation (e.g., agricultural capability classes with low agricultural value, under the Ministry of Agriculture Decree No. 83, following USDA standards), (iii) excluded shrublands and areas lacking native forest regeneration capacity using vegetation belts (Luebert and Plischoff 2017) as an ecological viability screen, and (iv) excluded public and private conservation areas that are not counted toward Chile's afforestation strategy under the NDC. Finally, conversion costs and constraints were set primarily by Chilean legislation. Full hyperparameter settings are reported in Appendix A6.

3.4. Ensemble simulations, synthesis, and spatial analyses

Given that GeoSOS-FLUS includes stochastic allocation, we generated 100 simulations per scenario -a commonly adopted range in stochastic LULCC applications - and synthesized the results using frequency-based summaries, as this number was sufficient to ensure stability in the resulting frequency maps. We produced afforestation change-frequency maps and identified high-confidence change areas based on the distribution of change frequency across simulations. To align outputs with Chile's afforestation strategy, we filtered candidate afforestation patches using a minimum patch size threshold (5 ha) and reported the resulting spatial patterns (details and thresholds in Appendix A7).

To compare the spatial patterns of afforestation scenarios, we computed landscape metrics using PyLandStats (Bosch 2019), aggregating these metrics at the catchment scale and classifying them according to water stress using the Water Scarcity Index (WSI; Boisier et al., 2024). (See section 3.2)

4. Results

4.1. Methodological performance of the proposed framework

Before presenting the Chilean case-study outcomes, we first assess whether the proposed framework improves the evaluation of afforestation policies compared to conventional FLUS applications. The FT-Transformer model demonstrated better predictive performance than the baseline ANN used for land-use suitability classification. On the test set, the FT-Transformer achieved an overall accuracy of 0.772, compared to 0.720 for the baseline ANN, representing an absolute improvement of 5.2%.

The results of the frequency-based ensemble showed that only a limited part of the simulated afforestation was spatially robust with high-certainty changes (P99) accounting for only 15.8% of the patches in the trend scenario and 27.2% in the incentive scenario. In contrast, when using the median frequency threshold (> 0.5 , P51), the forested area reached 137,089 ha in the trend scenario and 149,342 ha in the incentive scenario, representing an 8.9% increase with incentives.

Together, these results show that the proposed framework improves suitability classification compared to the baseline ANN and enables the identification of both total and high-certainty projected afforestation patterns across scenarios. This distinction is critical, as it shows that a substantial share of projected afforestation is not spatially robust, which would not be captured under single-run simulations.

4.2. Spatial analysis of afforestation scenarios

We found that the total area available for afforestation in the study area is 3,635,338 hectares, including shrubs and bushes, grasslands, annual crops, and evergreen grasslands and pastures. Thus, the commitment corresponds to afforesting 5.5% of the available area (Fig. 3).

In both scenarios, afforestation tended to concentrate near existing forests and protected areas, although some isolated patches also emerged far from pre-existing forest cover (Fig. 4). In the trend scenario, patches were smaller and more numerous, while in the incentive scenario, patches were fewer and larger (Table 1).

Analysis of afforestation patch configuration (Table 1) reveals less fragmentation of new forests in the incentive scenario, with a 14.5% decrease in the number of patches and a 21.5% decrease in patch density, compared to the trend scenario. This scenario also shows greater connectivity, with a 236.8% increase in the largest patch index (LPI), a 325% increase in effective adequate mesh size (EMS), and a shorter distance to the nearest neighbor (-11.8%).

Table 1
Landscape metrics for both scenarios. The metrics were calculated after segmenting pixels with a frequency greater than 0.5. We used the Python library pylandstats. The variation was calculated with respect to the trend scenario.

Metric	Trend	Incentive	%Δ
Shape index	1.776	1.808	1.79%
Fractal dimension	1.095	1.097	0.14%
Effective mesh size	143.66	610.525	325.00%
Number of patches	6490	5548	-14.50%
Patch density	4.729	3.712	-21.50%
Largest patch index	1.205	4.059	236.80%
Area means	21.144	26.936	27.40%
Area standard deviation	50.896	125.379	146.30%
Area coef. variation	240.71	465.462	93.40%
Perimeter area ratio	212.98	212.841	-0.06%
Landscape shape index	155.6	147.633	-5.12%
Core area	3.3	5.611	70.00%
Core area index	5.58	6.155	10.30%
Euclidean nearest neighbor	818.14	721.787	-11.80%

The shapes of the patches are similar in both scenarios (shape index and perimeter-area ratio). However, the pattern is somewhat more aggregated in the incentive scenario due to a slight decrease in Landscape Shape Index (LSI) (-5.1%). Therefore, the incentive scenario tends to consolidate afforestation into fewer, larger, and more connected patches, increasing the core area and spatial continuity.

These differences illustrate how policy incentives affect not only the extent but also the spatial organization of land-use change, which has implications for ecosystem functioning and planning.

4.3. Hydrological risk

According to the water-stress classification of the basins in the study area (Boisier et al. 2024), the low-stress basins have the largest total surface area in both scenarios (Fig. 5). However, the highest percentage change in incentive afforestation occurs in catchments with medium to high stress (267%), raising concerns about the impact this new coverage could have on the catchment water balance.

Incentives do not broadly redistribute afforestation toward more stressed watersheds. Figure 5 shows that the incentive scenario does not generate a uniform redistribution of afforestation across the study area. Instead, relative gains are concentrated in a limited subset of catchments, while large portions of the landscape show little difference between scenarios. This suggests that the incentive primarily intensifies afforestation in selected basins rather than creating an entirely new way of expansion. Furthermore, we show that, in both scenarios, most afforestation would occur in watersheds with low water stress, whether considering the classification of water-stress degree in watersheds under an average climate (1960s to 2010s) or an extreme climate (2010s-2020s) (See Fig. 1). Considering climates like that of the period between 1960 and 2010, an incentive for afforestation would lead to a 263.5% increase in forest area in basins with medium-high water stress (at the 50th percentile of simulations; Fig. 6). This increase also implies greater afforestation density in smaller watersheds. Watersheds with medium-low water stress also show an increase in forested areas (5.4%). Watersheds with high stress would not be afforested in any scenario, and under this climate, there are no watersheds with extreme stress.

In the context of the megadrought (2010s-2020s), the largest increases of afforested area are concentrated in watersheds that would now be under high stress (+ 260.5%; from 4,633 to 16,703 ha; density from 0.168 to 0.605 ha/km²) and medium-high stress (+ 196.5%; from 370 to 1,096 ha; density from 0.034 to 0.099 ha/km²), in addition there is slight afforestation in watersheds under extreme stress (70–100%; from 0 to 138 ha). The highest forest density occurs in a scenario with watershed-level incentives under high stress, based on the WSI for the 2010s period.

This highlights that policy-induced shifts in spatial allocation can alter exposure to environmental risks even when aggregate outcomes appear favorable.

5. Discussion

This section discusses the implications of the results for afforestation planning and land-use policy. We focus on three key dimensions: the role of uncertainty in spatial simulations, the feasibility and spatial configuration of afforestation under contrasting policy scenarios, and the hydrological and ecological trade-offs associated with forest expansion. By linking methodological advances with policy-relevant outcomes, we assess how the proposed framework contributes to a more robust and spatially explicit evaluation of afforestation strategies.

5.1. Ensemble certainty and methodological implications for planning

This study shows that explicitly accounting for spatial uncertainty in land-use simulations can substantially change the evaluation of afforestation feasibility and associated environmental risks. Rather than relying on a single simulation run, the ensemble approach reveals the variability of spatial outcomes, distinguishing between changes that are consistently projected and those that are more

uncertain. This distinction is relevant for planning, as high-certainty afforestation zones provide a more reliable basis for spatial prioritization, while low-frequency changes should be interpreted with caution. More broadly, these results reinforce that no single model run should be considered definitive, and that approaches incorporating uncertainty offer a more robust basis for evaluating land-use policies (O' Ryan et al. 2019; Luo et al. 2023).

This is particularly relevant because uncertainty quantification is still relatively uncommon in FLUS-based applications. Ensemble synthesis through frequency maps and high-certainty thresholds, such as the 99th percentile, can therefore improve the transparency and practical value of spatial planning exercises (Ma et al. 2022; Jin et al. 2023). In our case, the fact that high-certainty changes accounted only a limited fraction of simulated patches reinforces the importance of distinguishing between the total modeled footprint of afforestation and the smaller subset of changes that can be considered spatially robust. Together with the improved suitability representation provided by the FT-Transformer, the ensemble approach strengthens the robustness of spatial projections used for policy evaluation.

At the same time, these results are still sensitive to the quality of land-cover inputs, the static nature of several drivers, and expert-defined hyperparameters. These limitations mean that simulations should not be interpreted as deterministic forecasts, but rather as scenario-based spatial assessments that support prioritization, screening, and discussion of trade-offs under contrasting policy assumptions.

5.2. Feasibility and spatial configuration of afforestation under contrasting scenarios

Although the afforestation target is only a small fraction of the eligible land base, our results show that it cannot be fully distributed under the observed transition dynamics, legal constraints, and land-use competition. This distinction between land that is theoretically suitable for afforestation and the likelihood of its being distributed is important, since national afforestation commitments may appear achievable if assessed solely as gross area targets, but prove difficult to meet in practice due to spatial constraints and competitive allocation processes. This is consistent with broader critiques that highlight how maps of restoration opportunities often overestimate the available land area when factors such as competition for land use, land tenure, governance, and social constraints are considered (Rakotonarivo et al. 2023; Fesenmyer et al. 2025). In this sense, the large, simulated differences suggest that viability should be assessed not only on land availability, but also on whether the landscape can accommodate the expansion of land cover under current forestation dynamics.

Regardless of total area, the two scenarios also differed in the spatial configuration of afforestation. Simulated afforestation tended to form concentrated patches, especially in the scenario with incentives, which resulted in fewer but larger and better-connected patches. This configuration could improve carbon outcomes, as larger plots typically have a lower edge-to-area ratio, which reduces exposure to surrounding environments, which are generally warmer, drier, and more variable than the interior of the forest (Matlack 1993; Weathers et al. 2001). Fragmentation has also been associated with reduced carbon storage near forest edges, with reported declines of approximately 9–50% within the first 100 m

from the edge (Laurance et al. 1997; Chaplin-Kramer et al. 2015). Although some temperate studies have reported higher growth rates near edges, such gains may decline rapidly under thermal stress, highlighting the sensitivity of edge-mediated carbon dynamics (Reinmann and Huttyra 2017; Smith et al. 2018).

At the same time, afforestation was not distributed uniformly. Some simulated patches emerged far from established forests, which can be interpreted as plausible outcomes of CA-based allocation, where nonlinear neighborhood interactions and competition among land uses generate spatially non-intuitive patterns (Wolfram 1984). However, a second consistent pattern was the concentration of simulated afforestation near existing forests and protected areas. Part of this proximity may reflect processes closer to regeneration than active planting. However, it stays relevant from a planning perspective because adjacency to established vegetation can buffer wind, radiation, and temperature extremes, thereby favoring establishment success (Hersperger and Forman 2003; Holl and Brancalion 2020). In addition, regeneration from local seed sources may preserve greater genetic diversity and resilience than simpler planting strategies (Ruñgis et al. 2019).

The incentive scenario also showed a northward redistribution of afforestation, consistent with the scenario design, which prioritized forest types with the highest carbon sequestration potential found in this area, based on the sequestration parameters used by the Chilean government for its inventories. However, this change should not be interpreted as the sole effect of the incentive predictor in an absolute sense. The inclusion of incentives can reshape the area of suitability through interactions with other predictors, leading FLUS to redistribute expansion in ways that are difficult to interpret theoretically. This highlights that incentives affect not only the area of afforestation but also its spatial distribution, with consequences for patch structure, ecological function, and land use planning.

5.3. Hydrological, ecological, and social safeguards for afforestation planning

From a planning perspective, the simulated expansion cannot be evaluated solely on carbon grounds. In our results, most afforestation remained concentrated in watersheds with low water stress, but the incentive scenario disproportionately increased afforestation in more stressed basins, particularly under megadrought conditions. This pattern is consistent with a broader carbon-water tradeoff: afforestation may enhance CO₂ uptake while simultaneously increasing evapotranspiration and interception losses, thereby reducing water availability at the watershed scale (Calder 1998; Farley et al. 2005; Lacombe et al. 2016; Feng et al. 2016).

This tradeoff is especially relevant in water-limited regions such as south-central Chile, where several studies have reported lower runoff in forested catchments than in grass- or shrub-dominated systems, as well as higher evapotranspiration in forest canopies (Huber and Lopez 1993; Echeverría et al. 2007; Olivera-Guerra et al. 2014; Galleguillos et al. 2021; Balocchi et al. 2023). Hydrological effects are often stronger in drier catchments and depend on where afforestation occurs within watersheds, for example, in headwater areas (Farley et al. 2005; Alvarez-Garreton et al. 2019; Galleguillos et al. 2021). In addition,

young stands may have high water demand, and establishment in water-limited environments may require irrigation, increasing both costs and pressure on already scarce water resources (Fuentes et al. 1994; Siyag 2014; Del Río San José et al. 2018). Although carbon dioxide fertilization due to enhanced atmospheric CO₂ concentration could partially offset some of these impacts, its magnitude and persistence remain uncertain (Norby and Zak 2011).

The viability gap found here also suggests that simply increasing incentives will not necessarily guarantee sustainable afforestation outcomes; therefore, incentive-based strategies should be viewed with caution. Without ecological and social safeguards, adverse consequences may emerge only in the longer term, even where short-term carbon gains appear favorable (Gómez-González et al. 2020, 2024). These supports moving beyond area-based targets alone and incorporating more practical targeting criteria, including where to plant, soil limitations, species choice, and establishment feasibility (Schachtsiek et al. 2014). Therefore, forest restoration must be integrated into land-use planning and account for the protection of existing ecosystems and multiple aims, not just carbon (Hua et al. 2024).

These safeguards are particularly important because, in general, afforestation may take place in ecosystems that are not naturally tree-dominated or that have still been treeless for extended periods (Veldman et al. 2019; Bond et al. 2019; Gómez-González et al. 2020). In such contexts, tree planting is not necessarily beneficial. Large-scale afforestation or plantation programs have been criticized for ecological and economic costs and, in some cases, limited mitigation value (Gómez-González et al. 2020; Moyano et al. 2024). Herbaceous and open biomes often support distinct biodiversity and ecosystem services that stay undervalued in climate policy, and denser tree cover may be incompatible with species and functions associated with open ecosystems (Veldman et al. 2019; Bond et al. 2019). Converting these systems to forest may also alter water resources, local livelihoods, and ecosystem dynamics (Alvarez-Garreton et al. 2019; Galleguillos et al. 2021; Smith et al. 2025).

Afforestation may also increase fuel loads and wildfire exposure, especially where forest expansion occurs across fragmented private ownership and near protected areas that depend on coordinated fire management. Under such conditions, unplanned afforestation may weaken the effectiveness of existing public wildfire strategies and increase the vulnerability of protected ecosystems to fire disturbance (Syphard et al. 2011; Gómez-González et al. 2020). Together, these hydrological, ecological, and governance dimensions show that afforestation commitments should be implemented through multi-criteria safeguards rather than solely through carbon-oriented area expansion. In practice, this means incorporating water-stress criteria, prioritizing restoration over simple tree-cover expansion, and promoting low-water-footprint and ecosystem-appropriate designs supported by ecophysiological metrics that explicitly address carbon-water tradeoffs (Medlyn et al. 2011; Ofosu et al. 2025). Furthermore, it is important to note that simple afforestation does not necessarily restore the structural complexity, native biodiversity, or ecological integrity of natural forests, which highlights the need to prioritize restoration over the mere expansion of tree cover (Jose 2024).

6. Conclusions

We developed a spatial simulation framework that combines FT-Transformer-based suitability estimation, FLUS allocation, ensemble uncertainty mapping, and watershed-level risk screening to assess feasibility, spatial configuration, uncertainty, and hydrological risk of afforestation commitments under contrasting policy scenarios. As a case study, we applied the framework to central and southern Chile, showing that the national target of 200,000 ha cannot be fully achieved under current transition dynamics, biophysical and legal constraints, and land-use competition, despite being only a small fraction of the eligible land base. This result highlights that afforestation commitments should not be evaluated solely on gross land availability, but also on spatial feasibility under realistic allocation processes.

Beyond total area, the simulations showed that incentives alter the spatial organization of afforestation by generating fewer, larger, and more connected patches, which may improve some carbon-related outcomes. However, ensemble results also showed that only a limited fraction of simulated change was highly certain, reinforcing the importance of distinguishing between the total modeled footprint of afforestation and the subset of changes that are spatially robust enough to support planning.

From a policy perspective, the results show that carbon-oriented incentives may increase afforestation while also shifting expansion toward hydrologically sensitive watersheds, particularly if a megadrought condition is present. Together with the ecological and social risks associated with afforestation in open or non-forest ecosystems, this suggests that progress toward national afforestation goals requires multi-criteria safeguards rather than area expansion alone. Prioritizing ecologically suitable areas, incorporating water-stress criteria, and favoring restoration-oriented strategies over indiscriminate tree-cover expansion are essential to avoid unintended outcomes.

More broadly, the proposed framework provides a transferable decision-support tool for evaluating afforestation programs in heterogeneous and hydrologically constrained landscapes. By combining land-use simulation, ensemble certainty mapping, and watershed-level risk screening, it helps translate national commitments into spatially explicit assessments of where afforestation is most feasible, where it is most uncertain, and where it may generate the greatest environmental trade-offs. This approach can be extended to other land-use interventions where spatial uncertainty and environmental trade-offs are critical, contributing to more transparent, robust, and spatially explicit policy evaluation.

Declarations

Competing Interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Author Contribution

J.H.-B.: Conceptualization, Methodology, Software, Formal analysis, Investigation, Data curation, Visualization, Writing – original draft. M.G.: Conceptualization, Methodology, Supervision, Validation, Writing – review & editing. R.O.: Conceptualization, Supervision, Validation, Writing – review & editing. All authors contributed to the interpretation of results, critically revised the manuscript, and approved the final version for submission.

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Data Availability

The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

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Figures

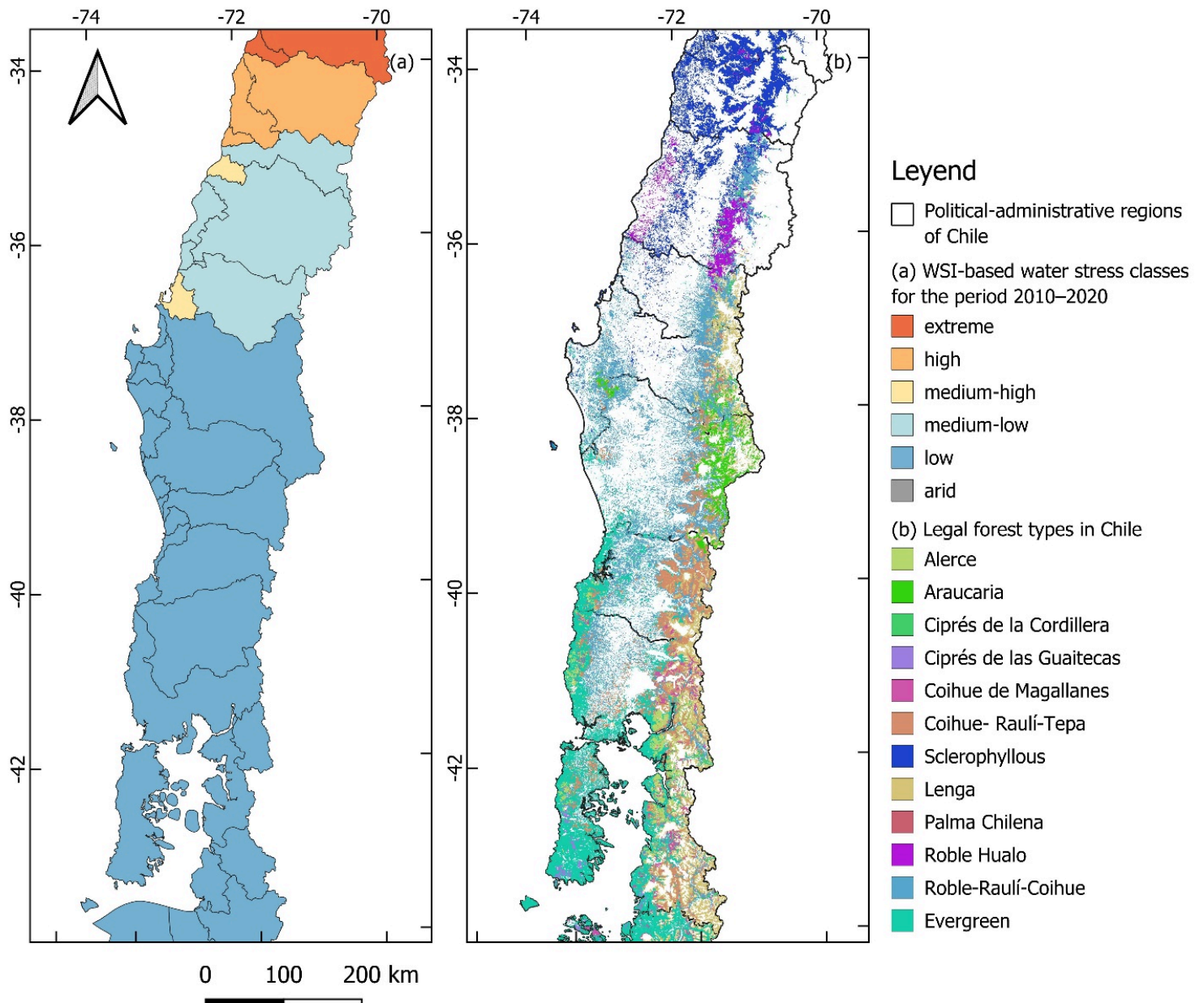


Figure 1

Water stress by basin and legal forest types in the study area. Panel (a) shows the average percentage of water stress index (WSI) for the period 2010-2020 (Boisier et al. 2024). Panel (b) displays the spatial distribution of forest types recognized under Chilean Decree Law No. 701 ([Decree Law No. 701, on Forest Promotion], 1974)

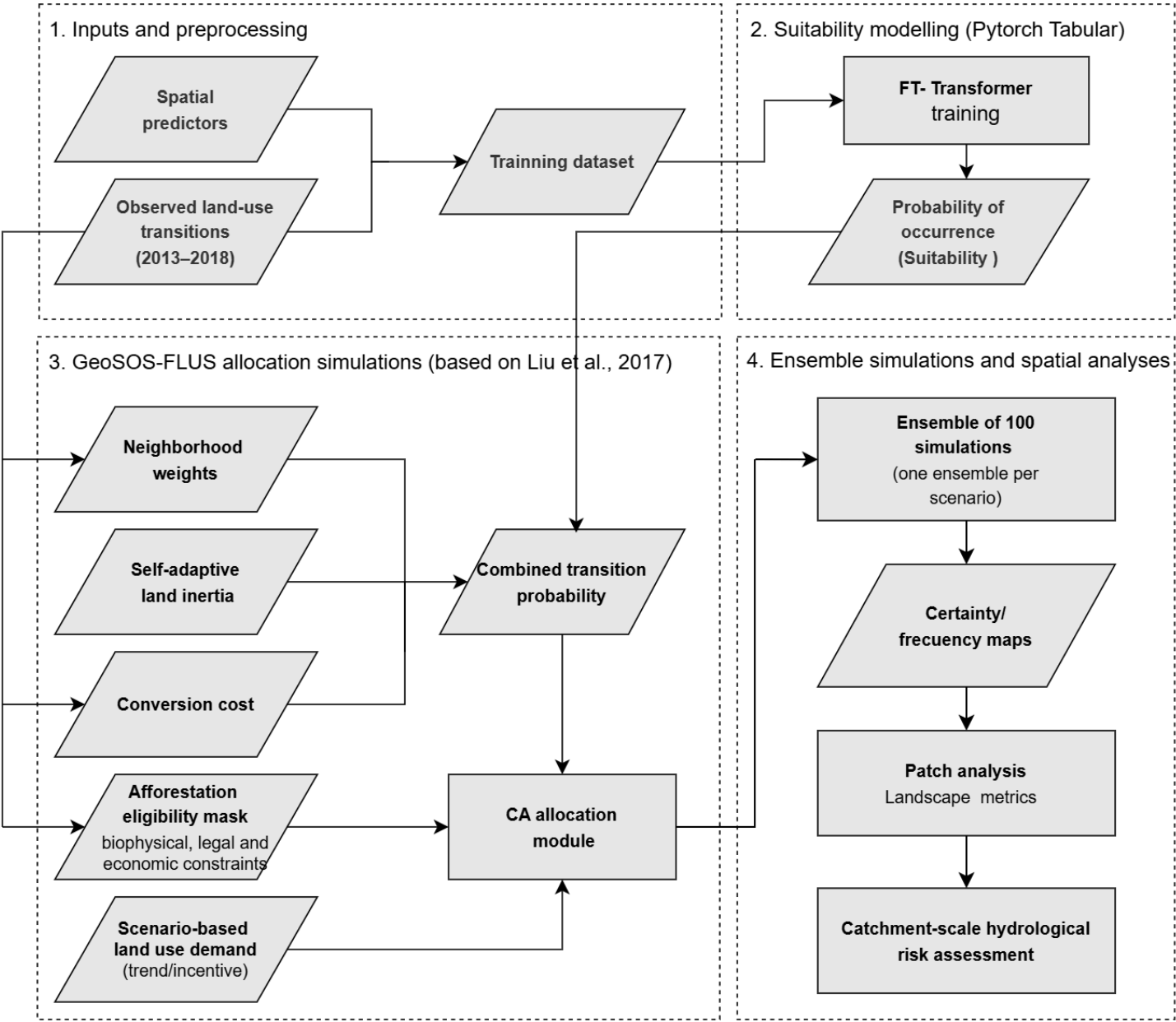


Figure 2

Modelling framework. Land-use and spatial information are used to train an FT-Transformer model to calculate the probability of occurrence. The probability of occurrence is integrated into the GeoSOS-FLUS CA module to generate a set of simulations for two afforestation scenarios. The dotted lines enclose the two modules that are coupled

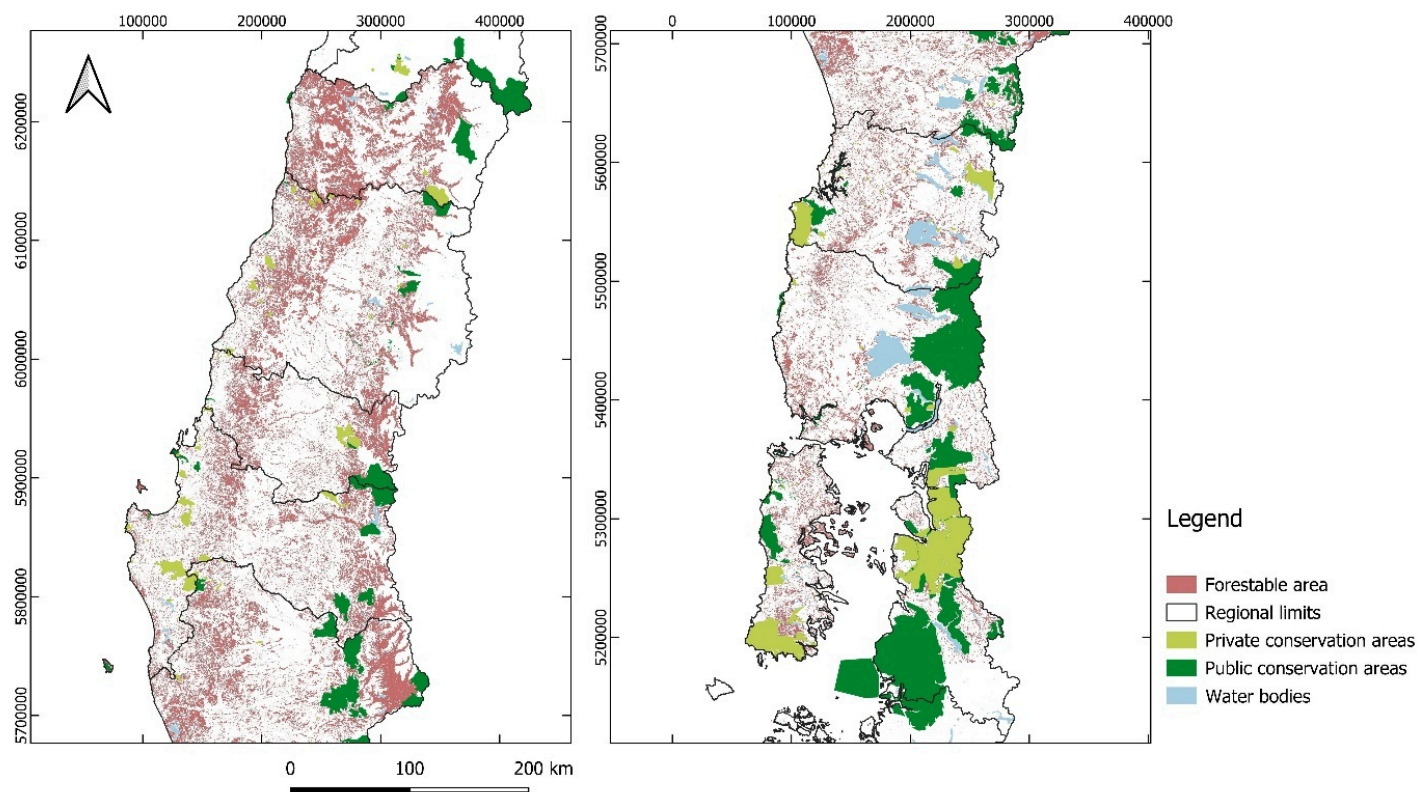


Figure 3

Spatial distribution of the potential forestry area

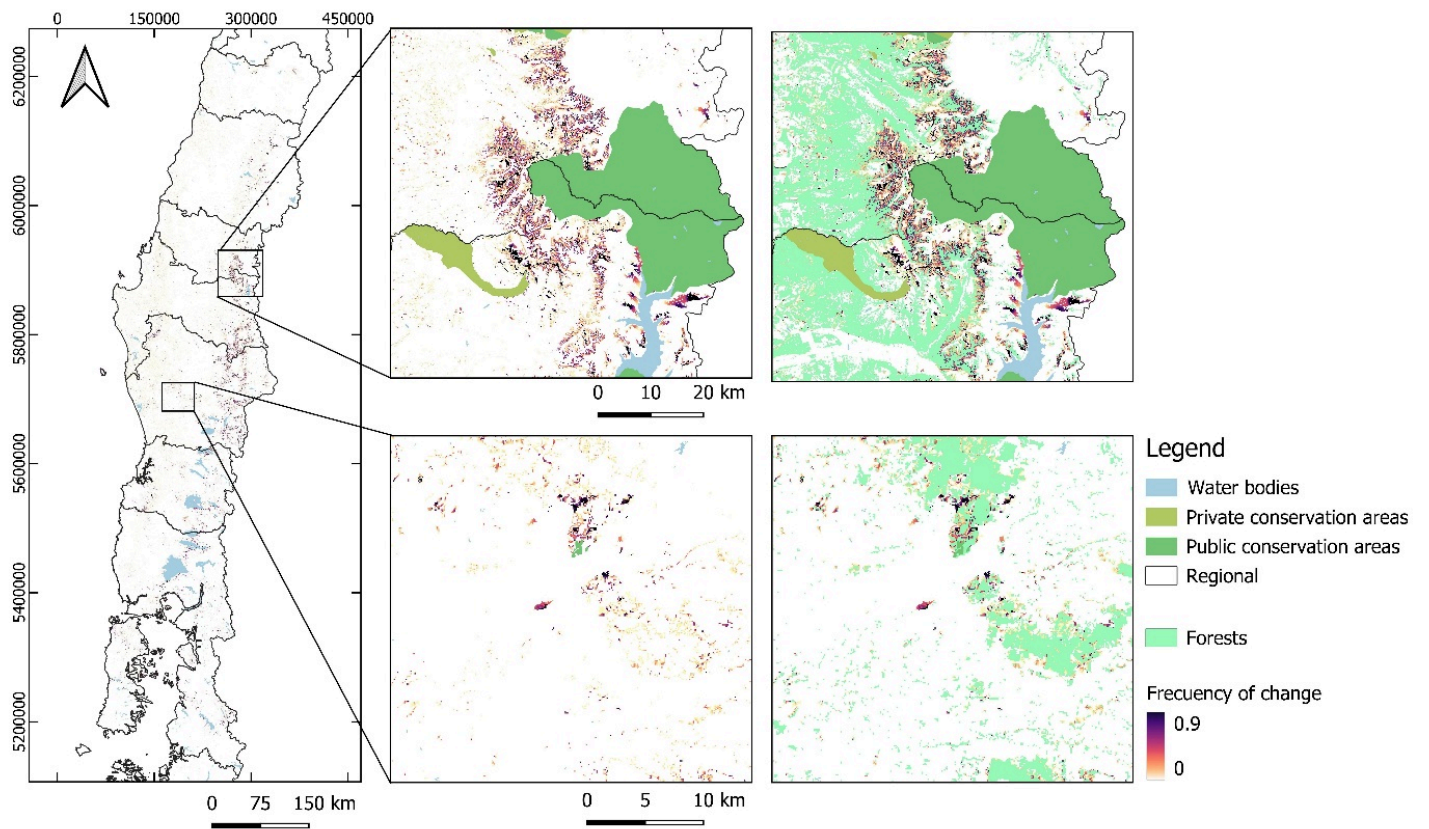


Figure 4

Frequency of change across 100 CA simulations under the trend scenario. The upper panels show changes near protected areas and pre-existing forests, while the lower panels show isolated emerging patches located away from these features

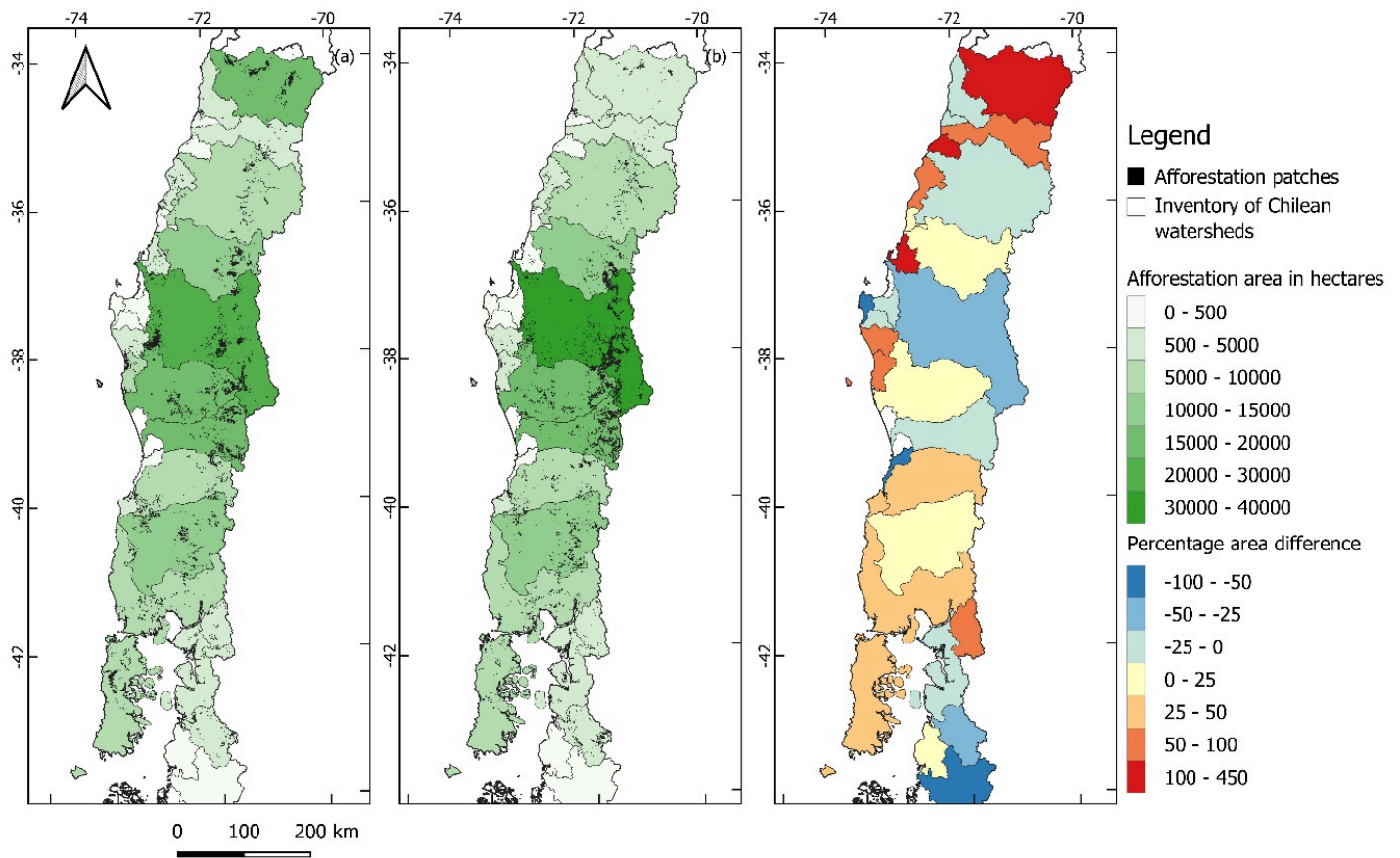


Figure 5

Spatial distribution of afforestation patches under the incentive and trend scenarios. Panels (a) and (b) show native forest patches representing afforestation, each with a minimum area of 5 ha as required by legal restrictions. Panel (a) shows the incentive scenario, and panel (b) the trend scenario. Panel (c) maps the percentage difference in afforested area by catchment relative to the trend scenario. Positive differences are spatially clustered rather than region-wide, indicating that incentives intensify afforestation in selected basins rather than broadly redistributing projected expansion

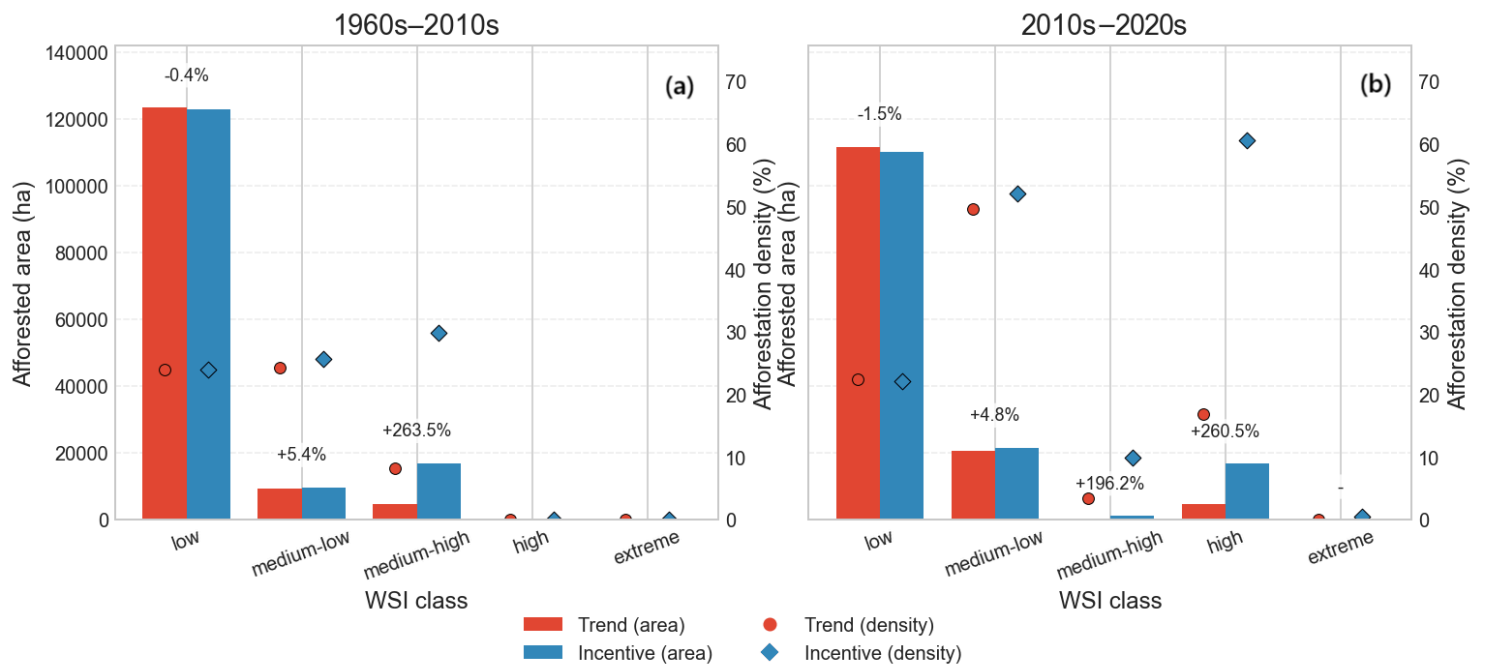


Figure 6

Afforested areas in catchments grouped by water stress level (WSI) under two climate periods. Bars show total afforested area, and points show forest density (ha km^{-2}) for the trend and incentive scenarios. Panel (a) shows 1960–2010 (Reference), and panel (b) shows the 2010s–2020s (Megadrought), used here as representative of megadrought conditions. Values above bars show the percentage difference between scenarios, and totals for each period are shown in bold. WSI classes are low (0–10%), medium-low (10–20%), medium-high (20–40%), high (40–70%), and extreme (70–100%)

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