Rural abandonment and its drivers in an irrigated area of Mendoza (Argentina)

Abandono rural y sus causas en un área irrigada de Mendoza (Argentina)

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Abstract

Rural abandonment is a global phenomenon promoted by biophysical, socio-economic, and socio-productive causes, leading to the disappearance of traditional agricultural practices and serious impacts on food security and local livelihoods. This phenomenon is more complex in drylands since the lost of productive land is unlikely to be recovered due to the limited availability of water resources. This study aimed to identify abandoned agricultural lands in a sector located east of the northern oasis of Mendoza (Argentina) and determine the main driving forces leading this process. The interdisciplinary perspective employed included the Normalized Difference Vegetation Index (NDVI) difference technique implemented on Landsat images, the boosted regression trees analysis of spatially explicit drivers, and a digital survey providing perception assessments from local producers and their technical advisors. Abandoned agricultural land has increased by 92% between 2002 and 2020, being accessibility, crop type, vulnerable living conditions of the local population, availability of irrigation water and labor, and the lack of profitability, the main drivers identified by both sources of information (spatial model and social perception). The proposed approach contributes to monitore productive resources and land-use planning with a holistic and long-term vision.

Keywords

agricultural land abandonment • NDVI difference technique • spatial modeling • social actors' perception

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Resumen

El abandono rural es un fenómeno global promovido por causas biofísicas, socioeconómicas y socioproductivas, que conduce a la desaparición de prácticas agrícolas tradicionales y tiene graves impactos en la seguridad alimentaria y los medios de vida locales. Este fenómeno es más complejo en las tierras secas, ya que es poco probable que se recuperen las tierras productivas perdidas debido a la disponibilidad limitada de recursos hídricos. Los objetivos de este estudio son identificar tierras agrícolas abandonadas en un sector del este del oasis norte de Mendoza (Argentina) y determinar las principales causas que conducen este proceso. Se empleó una perspectiva interdisciplinaria, que incluye la implementación de la técnica de diferencia del Índice de Vegetación de Diferencia Normalizada (NDVI) a partir de imágenes Landsat, el análisis de *boosted regression trees* para evaluar causas espacialmente explícitas y la evaluación de la percepción de los productores locales y sus asesores técnicos mediante una encuesta digital. Las tierras agrícolas abandonadas aumentaron un 92% entre 2002 y 2020 y los principales factores identificados por ambas fuentes de información (modelo espacial y percepción social) fueron la accesibilidad, el tipo de cultivo, las condiciones de vida vulnerables de la población local, la disponibilidad de agua de riego, la disponibilidad de mano de obra y la falta de rentabilidad. El enfoque propuesto busca contribuir al monitoreo de los recursos productivos y a un ordenamiento territorial con una visión holística y de largo plazo.

Palabras clave

abandono de tierra agrícola • técnica de diferencia del NDVI • modelado espacial • percepción de los actores sociales

Introduction

Rural abandonment is a global phenomenon detected in diverse regions, such as Europe, the United States, Asia, and Latin America (40). In general terms, rural abandonment is mainly promoted by three types of causes: biophysical (including factors such as elevation and slope, soil, or climate), socio-economic (including market incentives, migration processes, inefficient technology, land tenure, accessibility or characteristics of the producers) and, thirdly, socio-productive (associated with inadequate agricultural management leading to land degradation, overexploitation or loss of productivity) (35). Abandonment of productive land generally occurs in marginal agricultural areas and is associated with low levels of profitability (3, 40). This affects crop productivity even more and undermines investment, technological advancement, and the achievement of acceptable economic returns deepening the abandonment processes (37). Some authors see this change in agricultural land use as an opportunity for the restoration of ecosystem services and the recovery of biodiversity (19, 40), depending on the level of degradation. However, the social consequences of rural abandonment are extremely negative and include the disappearance of traditional practices, seriously impacting food security and local livelihoods (9, 12).

According to the UNCCD (2014), 52% of the world's agricultural land is moderately or severely affected by land degradation. Based on current consumption trends, it is estimated that agricultural production will need to increase by 70% globally, and 100% in developing countries, to meet population demands in 2050. Paradoxically, in Latin America, 50% of agricultural land could be affected by desertification by the same year (42). In this context and especially in drylands, inadequate management of productive resources puts the producers' subsistence and livelihoods at risk. Drylands account for 47% of the earth's land surface, covering hyper-arid, arid, semi-arid, and dry sub-humid climate regions where 2.6 billion people live (23). In Argentina, 63% of the national territory constitutes drylands (43). In these regions, where different irrigation systems transform arid ecosystems into cultivable irrigated areas known as "oases", water limits agricultural production. This limitation further complicates the phenomenon of rural abandonment. In arid to semi-arid Mendoza (Argentina) with 250 mm average rainfall, irrigation depends on water from snowmelt in the Andes Mountains, which feeds surface and underground water sources.

Thus, after years of gaining desert land through costly installations of irrigation systems, productive land is lost with low replacement prospects.

In this context, information systems have become valuable tools for managing datasets and identifying critical areas affected by land degradation processes (37). In particular, rural abandonment involves complex dynamics that, as such, must be addressed from an interdisciplinary perspective, including biophysical and socio-economic aspects. Therefore, the construction of spatial models in geographic information systems (GIS) and their statistical analysis makes it possible to associate local data on the occurrence of rural abandonment with variables that describe the biophysical environment and anthropogenic uses. Moreover, each variable has a relative assigned weight reflecting its influence on the process. This approach has allowed several case studies (12, 30, 33, 40). Given this multicausal problem, producer perspectives are valuable assets for understanding perceived constraints, threats, and opportunities (10, 13). Some studies have explored their perceptions of abandonment and plausible causes (4, 24, 31), while others have integrated quantitative data derived from spatial analysis with qualitative data derived from social studies to analyze landscape changes (14, 16, 32). Sustainability demands combining knowledge from different sources to achieve deeper understanding of any given problem.

Rural abandonment has been identified as an environmental problem in the oases of Mendoza but has not yet been thoroughly quantified (1). A previous study identified land-use changes between 2003 and 2019 in a district of the Guaymallén department located in the northern oases (15). Although the authors did identify the category of abandoned land, the employed methodology had limited scalability since it consisted of a visual interpretation of high-definition satellite images available on Google Earth. Both the observer training as well as image availability may hamper analysis extension to the entire oases. Another recent study identified land use and land cover changes between 1986 and 2018 at a larger scale, the Mendoza and Tunuyán River Basins (36). In this case, the methodology enabled an extensive analysis but did not explicitly identify the category of abandoned land. Regarding causes of productive land abandonment, Guida-Johnson *et al.* (2020) investigated the perception of local actors but did not intend to perform spatial modeling. Our study complements previous work and deepens the level of analysis. Rural abandonment is a complex process that can be addressed, quantified, and expressed spatially through an appropriate methodology. In this sense, detecting crop abandonment and investigating possible causes will significantly contribute to understanding rural abandonment dynamics at a local scale. Our objectives were: (1) to identify abandoned land in an irrigated area in the north of Mendoza province between 2002 and 2020 and (2) to determine the main biophysical, socio-economic, and socio-productive drivers considering spatial modeling and social actors perception.

Materials and methods

Study area

The productive activities in Mendoza province (Argentina) are concentrated in three oases: north (irrigated by the Mendoza and lower Tunuyán rivers), center or Valle de Uco (irrigated by the upper Tunuyán river), and south (irrigated by the Diamante and Atuel rivers). In particular, the northern oasis can be divided into two zones with distinctive characteristics: east and center. The study area was the department of General San Martín (figure 1, page 38), good representative of the process of rural abandonment in eastern Mendoza. Located in the Mendoza plain, the department has an area of 1,507 km^2, with its capital city located 43 km from the provincial capital. San Martín is characterized by a great diversity of soils and subsoil water availability, which makes it suitable for crop development. The predominant natural vegetation is xeric, psammophilous, or halophilous shrub steppe, scrubland, and some small relicts of forest (5, 44). Land degradation processes affect the entire area and accelerate the natural phenomena of water and wind erosion (2). According to the latest census (18), the department has almost 140,000 inhabitants and a population density of 92.8 inhabitants/km^2, most of them concentrated in the capital city, and the rest distributed in small or medium-sized towns surrounding the main city.

Approximately 60% of the population over 5 years of age attended some educational establishment (18). Considering population density, health and service infrastructure, and logistics, San Martín is the main department of eastern Mendoza. However, inequalities between urban and rural populations regarding access to social infrastructure (such as drinking water, public transportation, sewage, natural gas, electricity, or waste collection) are profound. Considered one of the main grape-growing areas in the country, the main economic activity is viticulture, followed by olive and fruit production, as well as horticulture. The main economic units are associated industries and family businesses. Historically, urban expansion over rural areas has been carried out in a chaotic or disorderly manner, transforming lands with high agricultural potential and accentuating territorial imbalances.

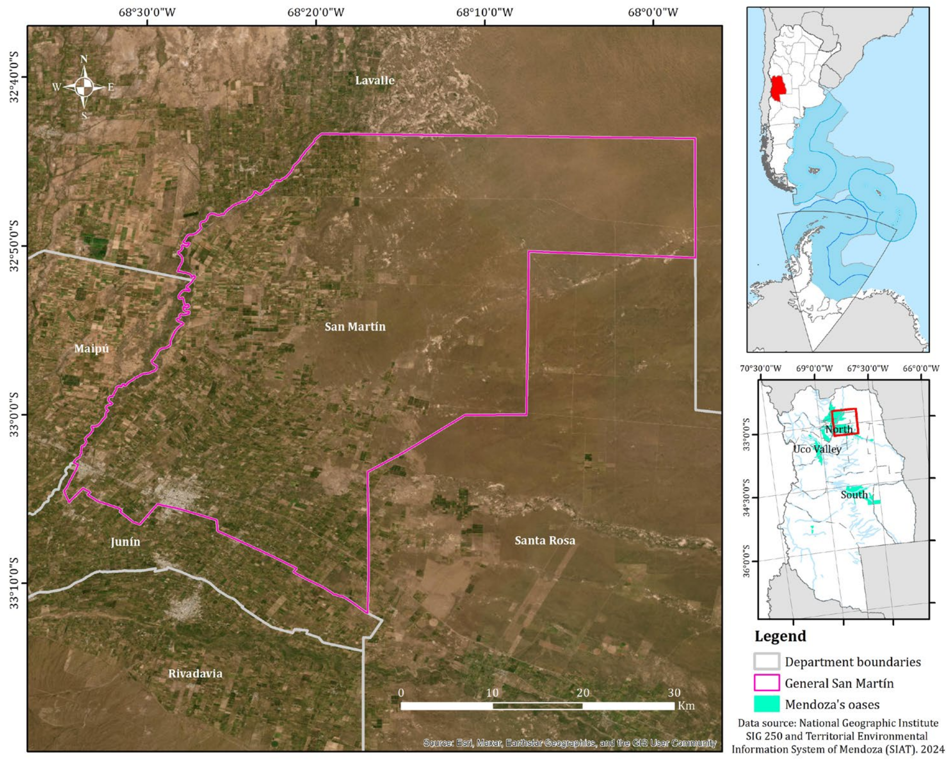

Figure 1. Location of the study area.

Figura 1. Localización del área de estudio.

Detecting rural abandonment

A land-use land-cover (LULC) map was used as a reference and satellite images were analyzed by the Normalized Difference Vegetation Index (NDVI) difference technique to detect changes (22, 27, 41). The production map of Mendoza province constituted our reference. The map, prepared and provided by the Institute for Rural Development [Instituto de Desarrollo Rural, IDR], was created by visual interpretation of high-resolution images available on Google Earth. LULC categories were: abandoned land, non-productive tree cover, fruit trees, vegetables, natural vegetation, olives, pastures, other uses (including swimming pools, and campsites), urban, vines, and vines with olives.

The NDVI difference technique is one algebraic change detection technique, simple and easy to implement and interpret (25). Considering the reference map, the study period was defined between 2002 and 2020. This study used two atmospherically corrected satellite images transformed to surface reflectance: one from the Landsat 5 TM sensor obtained in 2002 and one from Landsat 8 OLI obtained in 2020. A preliminary assessment of monthly NDVI variation associated with different LULC categories allowed image date selection. In

December 2019, 200 field points were surveyed. The largest differences between cultivated and abandoned land were recorded in February when both selected satellite images were obtained. The NDVI was calculated for each scene from the reflectance values in the near-infrared (NIR) and red (R) regions, following Eq. (1).

$$NDVI = \frac{NIR - R}{NIR + R} \quad (1)$$

The NDVI difference was then calculated (ΔNDVI) (Eq. 2). In the resulting image, pixels were divided into no-change pixels with values around zero and change pixels with values sufficiently far from zero (positive and negative) (29).

$$\Delta NDVI = NDVIt2 - NDVIt1 \quad (2)$$

Where NDVIt2 is calculated for the Landsat scene obtained in 2020 and NDVIt1 is calculated for the Landsat scene obtained in 2002. One key issue is threshold definition, *i.e.*, which value change is to be considered significant. In general, thresholds associated with different numbers of standard deviations for NDVI values (σ) are tested, visually choosing the one that best detects changes (27, 29, 41). In this study, four thresholds were tested: 1σ, 1.5σ, 2σ, and the one determined by the Jenks natural breaks classification method.

The changed pixels interpretation was based on comparisons with the reference map considering whether ΔNDVI was positive or negative. Detection of abandoned rural land was performed as detailed in Table 1: no-change pixels preserve their category, whereas change pixels are converted into abandoned land (AL), cultivated land (CL) or not cultivated land (NCL). A rural abandonment map was produced for each ΔNDVI threshold. Original LULC categories from the reference map were regrouped into abandoned land, cultivated land (including fruit trees, vegetables, olives, pastures, vines, and vines with olives) and not cultivated land (non-productive tree cover, natural vegetation, other uses, and urban).

Table 1. Criteria to detect abandoned agricultural land based on NDVI difference technique and a reference map.

Tabla 1. Criterios para detectar tierra agrícola abandonada basándose en la técnica de diferencia del NDVI y un mapa de referencia.

<table>
<tr><th colspan="2" rowspan="3">Reference map</th><th colspan="3">Rural abandonment map</th></tr>
<tr><th>No-change pixels</th><th colspan="2">Change pixels</th></tr>
<tr><th>ΔNDVI near 0</th><th>Significantly (-) ΔNDVI</th><th>Significantly (+) ΔNDVI</th></tr>
<tr><td>Abandoned land</td><td>AL</td><td>AL</td><td>AL</td><td>CL</td></tr>
<tr><td>Fruit crops</td><td rowspan="6">CL</td><td rowspan="6">CL</td><td rowspan="6">AL</td><td rowspan="6">CL</td></tr>
<tr><td>Vegetable crops</td></tr>
<tr><td>Olive crops</td></tr>
<tr><td>Pasture</td></tr>
<tr><td>Vine crops</td></tr>
<tr><td>Vine and olive crops</td></tr>
<tr><td>Natural vegetation</td><td rowspan="4">NCL</td><td>NCL</td><td>NCL</td><td>CL</td></tr>
<tr><td>Unproductive tree cover</td><td rowspan="3">NCL</td><td rowspan="3">NCL</td><td rowspan="3">NCL</td></tr>
<tr><td>Other land uses</td></tr>
<tr><td>Urban</td></tr>
</table>

The ΔNDVI thresholds were assessed by validating the rural abandonment maps from ground truth data. Three campaigns surveying GPS points in the study area were conducted in December 2019, March 2021, and June 2021, collecting 537 sample points. An error matrix was constructed for each map with these data, while descriptive statistics were calculated. Total accuracy represents the proportion of reference points correctly classified. Producer's accuracy indicates the probability of a reference point correctly classified, *i.e.* how properly a particular area can be classified. Finaly, user's accuracy estimates the probability of a point on the map representing the class on the ground (6). A rural abandonment map was selected based on statistics, and the area associated with each category was calculated.

Identifying rural abandonment drivers

Rural abandonment drivers were identified and assessed using two sources of information: a spatial model, and social actors perceptions. A GIS model weighed the relative contribution of spatially explicit driving forces (12, 33). To that end, 2000 points were randomly plotted on the selected rural abandonment map to gather data and run a machine learning algorithm. For each point, the response variable was presence or absence of rural abandonment. Predictor variables were compiled from available geo-referenced secondary data of three types, namely attributes of the biophysical environment, and socio-economic and socio-productive aspects. The former included: (1) elevation obtained from Shuttle Radar Topography Mission (SRTM) data (20); (2) aridity index values, freely available from the Territorial Environmental Information System of Mendoza [Sistema de Información Ambiental Territorial de Mendoza] (38); and (3) frequency of storm damage events recorded during 2002-2017, available at the Directorate of Agriculture and Climatic Contingencies of Mendoza website [Dirección de Agricultura y Contingencias Climáticas de Mendoza] (7). The socio-economic and socio-productive aspects included: (4) the original type of crop obtained from the productive map of Mendoza provided by the Institute for Rural Development; (5) population density, that is the number of inhabitants registered by census unit, (6) the percentage of households with unsatisfied basic needs (UBN), including overcrowded homes, precarious housing, poor sanitary conditions, non schooled children or household head without complete schooling, and (7) percentage of the working-age population who only reached primary education level (*i.e.* those not meeting certain minimum conditions - secondary education – in order to access formal employment), with data obtained from the National Census of Population, Households and Dwellings 2010 [Censo Nacional de Población, Hogares y Viviendas 2010] (17); (8) the Euclidean distance to national and provincial roads available in the Territorial Environmental Information System of Mendoza (39); (9) the Euclidean distance to irrigation network and (10) to groundwater extraction wells and (11) the density of canals and (12) wells, with data provided by the General Department of Irrigation of Mendoza [Departamento General de Irrigación (DGI)]. The values of all the predictor variables were recorded at each random point.

The data were analyzed by boosted regression trees (BRT) (30, 40) through R software (34) using the dismo package version 1.3-5. This approach uses boosting to combine large numbers of relatively simple tree models to optimize predictive performance and identify relevant variables, explaining an observed pattern (11). Model parametrization was performed with tree complexity, which controls the number of fitted interactions; the learning rate, which determines tree contribution to the model; and the bag fraction, which defines the proportion of data selected at each step (11). For this, different combinations of tree complexity (1 to 9), learning rate (0.01, 0.005, 0.001, and 0.0005), and bag fraction (0.5 and 0.75) were tested (21, 28). Model selecting criteria intended to maximize the explained deviance, *i.e.* variability explained by the model, and minimized the difference between the training data AUC score and the cross-validated AUC score, to reduce overfitting (8, 11). Variables with relative influence under the expected by chance (100 divided by the number of explanatory variables) were considered non-relevant for interpretation (30). Considering the 12 variables tested, in this case, the relative influence threshold was 8.33%.

Regarding social perception, questions addressed abandonment causes and the areas and years in which the phenomenon was evident in the department of San Martín. Focus was placed on producers and their technical advisors. For this purpose, a pilot study was conducted and a qualitative online survey was administered through a Google Form. A total of 50 producers and/or advisors from San Martín were contacted through different social networks. The survey consisted of five open and closed questions on (1) major drivers of rural abandonment in the department of San Martín (considering depth of the water table, crop type, population density, access to road network, and water and labor availability), (2) additional environmental or socio-economic and cultural factors impacting the abandonment process; (3) localities with abandoned agricultural plots, (4) localities in which this process occurred with greater intensity between 2002 and 2020, and (5) the time in which the process of abandonment was intensified (dividing the period under analysis into three equal parts: 2002-2008, 2009-2014 or 2015-2020). The surveys were analyzed using descriptive statistics and compared with the spatial analysis.

Results

Rural abandonment maps derived from the four ΔNDVI thresholds found values of overall accuracy between 0.70 and 0.77 (table 2). The differences between these values lay in the accuracy with which abandoned and cultivated land was identified. At one extreme, the map derived from the threshold given by the Jenks Natural Breaks function correctly classified 63% of sample points identified as abandoned land (producer's accuracy 0.63), while it misclassified 29% of sample points identified as cultivated land (producer's accuracy 0.71). On the opposite, the map derived from the threshold defined as 2σ, correctly classified 36% of sample points identified as abandoned land (producer's accuracy 0.36), with 95% of the sample points identified as cultivated land correctly classified (producer's accuracy 0.95). Considering this paper aims to detect rural abandonment in the study area, the Jenks Natural Breaks function was selected as ΔNDVI threshold.

Table 2. Total, producer's, and user's accuracy associated with the four rural abandonment maps derived from assessed ΔNDVI thresholds: Jenks Natural Breaks (NB), 1σ, 1.5σ y 2σ.

Tabla 2. Exactitud total, del productor y del usuario asociadas a los cuatro mapas de abandono rural generados a partir de los umbrales de ΔNDVI analizados: Quiebres Naturales de Jenks (NB), 1σ, 1.5σ y 2σ.

ΔNDVI threshold	Total accuracy	Producer's accuracy			User´s accuracy		
		Abandoned land	Cultivated land	Not cultivated land	Abandoned land	Cultivated land	Not cultivated land
NB	0.70	0.63	0.71	0.84	0.50	0.82	0.79
1σ	0.75	0.50	0.86	0.84	0.61	0.80	0.81
1.5σ	0.77	0.42	0.93	0.84	0.71	0.78	0.79
2σ	0.77	0.36	0.95	0.84	0.74	0.77	0.79

According to the selected rural abandonment map, abandoned land increased by 92% during the study period. This was calculated considering the 13,492 ha in the reference map which was incremented to 25,869 ha in the 2020 rural abandonment map (table 3, page 42). Four areas concentrate abandoned land in north, central-west, central-east, and south San Martín (figure 2, page 42).

Table 3. Area (ha) for each land use category in the reference map (Mendoza productive map elaborated by IDR) and in the rural abandonment map (detected with NDVI difference technique). Variations are indicated in %.

Tabla 3. Área (ha) para cada categoría de uso de suelo en el mapa de referencia (mapa productivo de Mendoza elaborado por el IDR) y en el mapa de abandono rural (detectado con la técnica de diferencia del NDVI). Se indican los cambios (%) entre ellos.

Land use category	Reference map	Rural abandonment map	Changes (%)
Abandoned land	13,492	25,869	+92
Cultivated land	42,397	30,169	-29
Non-cultivated land	11,941	11,791	-1

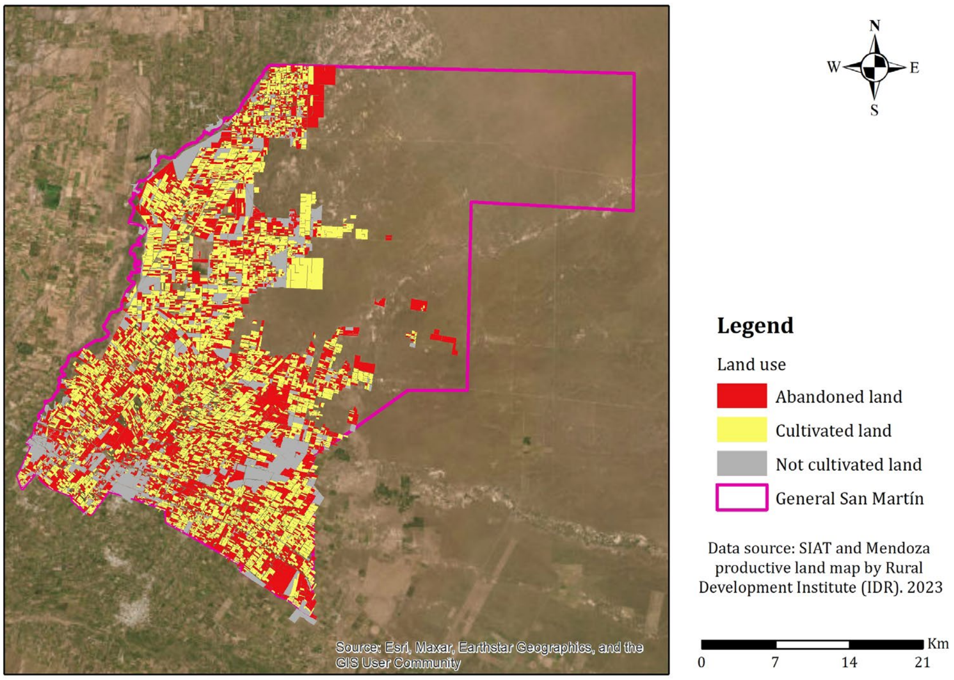

Figure 2. Rural abandonment map for the study area in 2020.

Figura 2. Mapa de abandono rural para el área de estudio en 2020.

The spatial analysis indicated that the Euclidean distance to national and provincial roads, crop type, percentage of households with unsatisfied basic needs (UBN), distance to wells and irrigation canals, and density of canals and groundwater extraction wells mostly explained the spatial distribution of abandoned land in the study area (table 4, page 43). The model explained 24.62% of the observed variability, probably due to the complexity of the analyzed problem. Distance to roads indicates accessibility to agricultural plots and accounts for management and harvesting difficulties. The crop would be linked to production profitability and local, national, and international market incentives and disincentives. The percentage of UBN households provides idea of structural poverty conditions in which some producers or their employees live (*e.g.*, contractors who work and live on the farm and receive a share of production profit), as well as households of local people working in companies, especially during harvest time. Finally, the four variables associated with irrigation canals and groundwater extraction wells account for irrigation availability. It should be noted that, geographically, San Martín largely covers the eastern boundary of the northern oasis of Mendoza.

Table 4. Relative influence of explanatory variables for a BRT model developed with a tree complexity of 3, a learning rate of 0.005, and a bag fraction of 0.5. Explained deviance was 24.62%

Tabla 4. Influencia relativa de las variables explicativas para el modelo de BRT desarrollado con complejidad de árbol de 3, tasa de aprendizaje de 0,005 y *bag fraction* de 0,5. La devianza explicada fue del 24,62%.

Explanatory variable	Relative influence
Distance to roads	14.03
Type of crop	13.41
% Households with unsatisfied basic needs	12.86
Distance to wells	11.34
Channel density	10.78
Well density	10.63
Distance to channels	8.80
Elevation	6.32
Storm damage	4.29
Population density	4.05
% Working-age population with only primary education	3.35
Aridity index	0.15

Twenty-seven out of 50 producers and/or advisors completed the survey. Concerning the most important drivers of land abandonment in San Martín, 85% of the respondents pointed to irrigation availability, 81% to labor availability, and 67% to crop type, in agreement with the spatial analysis. When asked what other biophysical or socio-economic and cultural factors impact the abandonment process, 63% of the respondents pointed to a lack of profitability. In addition, 15% indicated difficulties associated with generational changes (in the words of the interviewees "(...) aging of the vine-growers and lack of desire of the new generations to continue with the activity"), 15% related to the regional economy and another 15% associated with insecurity (robberies, vandalism, and theft). When respondents were asked to indicate which districts in San Martín currently had abandoned plots, 74% indicated Montecaseros, 56% El Divisadero and 48% El Ramblón. Particularly, regarding the process between 2002 and 2020, 77% of respondents indicated Montecaseros, 58% El Ramblón and 46% El Divisadero. Data from spatial analysis and surveys point to Montecaseros and El Ramblón as two districts with intermediate evidence of rural abandonment (figure 3, page 44). Nueva California district was identified by some respondents, but showed strong evidence of rural abandonment in the spatial analysis. Conversely, El Divisadero was noted by numerous respondents but showed less evidence of abandonment in the spatial analysis. It is worth noting that southern districts, where a large amount of abandoned land was detected according to the rural abandonment map, were slightly mentioned by respondents. Finally, 65% of respondents indicated that rural abandonment has intensified in the last period, 2015-2020.

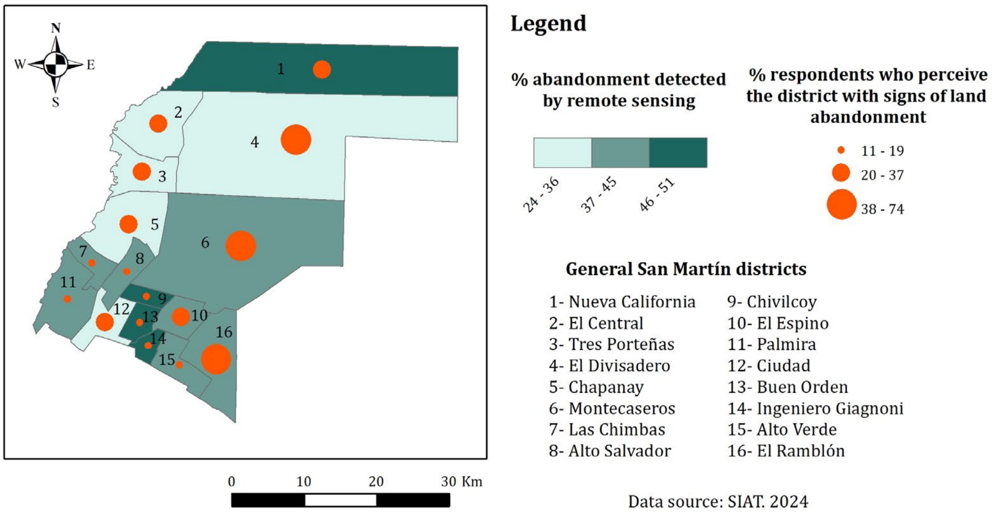

Figure 3. Location of rural abandonment in the study area according to remote sensing and respondents perception.

Figura 3. Localización del abandono rural en el área de estudio según la teledetección y la percepción de los encuestados.

Discussion

Rural abandonment is a global phenomenon associated with biophysical, socio-economic, and socio-productive causes (35, 40). In this respect, our results are in line with other studies associating this phenomenon with soil characteristics, topography and accessibility (12), the presence of soils with agricultural potential and agricultural subsidies (9), topography, accessibility, tractor and cropland density (30), crop yields and accessibility (33), physical environmental conditions, accessibility and global market pressures (3), equipment and materials costs and property taxes (24) or lack of state support, lack of occupation, demotivation of young people and lack of educational centers (31). In the study area, coincidences were found for both sources of information examined and also with these previous studies. According to the spatial analysis, rural abandonment would be associated with accessibility, type of crop, vulnerable living conditions of the local population, and availability of irrigation water. Whereas, the study of perception pointed to irrigation water and labor availability, type of crop, and the lack of profitability as major causes. Crop type is related to both profitability and agricultural management.

Regarding the territorial dimension, the NDVI difference technique showed that abandonment had increased in the analysed period at an alarming rate. All respondents acknowledged rural abandonment in the study area, recently intensified and associated with different districts in the department. The spatial pattern of rural abandonment showed some divergences between satellite image analysis and respondent perceptions. In some cases, both sources of information associated the process of agricultural land abandonment with different districts. It is worth noting that the sector where the greatest divergences were found (the south) overlaps with a zone defined by intense urban and industrial land uses in a matrix of cultivated areas. Two main, fast-growing cities in the department are located there: Ciudad de San Martín and Palmira. Moreover, the sector is crossed by National Route 7, one important commercial and tourist highway in the country, connecting the Atlantic and the Pacific oceans and integrating the Central Bioceanic Corridor. We could hypothesize that the development of this area interferes with the perception of rural abandonment. Although remote sensing analysis showed moderate to high levels of abandonment in south San Martín, respondents associated the phenomenon with locations farther away from these urban centers.

Remotely sensed information provides up-to-date databases supporting land management. Regarding rural abandonment, early detection of this type of change is particularly relevant to prevent and mitigate land degradation, which becomes the most efficient option. Thus, starting from an updated LULC map, detecting and monitoring changes may simplify and speed up the analysis (26). The methodology of LULC change detection used in this study resulted in a rapid application and easy implementation and interpretation. Compared with a previous study detecting abandoned land in a sector of the north oases (15), the implemented methodology could enable a larger-scale monitoring of the process. Therefore, the provided information could be useful for local authorities (among other social actors) for detecting the most compromised districts, speeding up the diagnosis, an invaluable phase of land use policy-making.

Rural abandonment becomes more complex in drylands, naturally vulnerable to degradation processes. In these regions, abandonment implies a loss of productive land and the entire associated technological system that is unlikely to be replaced due to the limited availability of water resources. Food security and local livelihoods are seriously at risk (9, 12). In this context, the complementation of quantitative data on landscape change with the perception of the local community is highly relevant and leads to understanding views, beliefs, and decisions of different social actors. This, in turn, is key to formulating public policies addressing processes of landscape change (14). On the other hand, studying the perception of social actors promotes a better understanding and interpretation of changes, enriches the explanation of driving factors, and leads to a comprehension of the complexity of the socio-economic and cultural context in which they occur (14, 16, 32). The incorporation of local community knowledge in decision-making contributes to strengthening alliances between the social actors involved, optimizing land-use planning processes with a holistic and long-term vision in pursuit of sustainable use of productive resources.

Conclusions

In the department of San Martín, located east of the northern oasis of Mendoza (Argentina), cropland abandonment increased by 92% between 2002 and 2020. As in other places around the world, this phenomenon is multi-causal. Accessibility, crop type, vulnerable living conditions of the local population, availability of irrigation water and labor, and lack of profitability constitute main drivers for land abandonment. Addressing this complex problem needs to integrate different sources of information and skills to develop public land-use planning policies that promote sustainable local development. The loss of productive land in drylands threatens food security, determining the urgency of preserving existing cultural and productive resources. The multidisciplinary approach implemented in this study used different methodologies and sources of information enabling a better understanding of the environmental problem. Moreover, it allowed defining differences between the perception of local social actors and the results derived from spatial analysis tools. Understanding and managing territorial complexity from an interdisciplinary perspective is essential to contributing knowledge to the local social reality.

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