Understanding the effect of three decades of land use change on soil quality and biomass productivity in a Mediterranean landscape in Chile

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ABSTRACT

Land-use and land-cover change (LUCC) can deeply alter soil quality (SQ), affecting important productivity functions like vegetation biomass. A further understanding of the history of LUCC is essential to explain natural or anthropic landscape cover. The Mediterranean region of central Chile has historically been affected by LUCC impacts on the vegetation gradient of the landscape, which ranges from natural cover to anthropic cover like grazing pastures and crop lands. The main objective of this study is to define the historical impact of LUCC on SQ in a Mediterranean landscape in central Chile. To conduct the study, historical LUCC trends between 1975 and 2011 were analyzed. A Soil Quality Index (SQI) was developed to comparatively assess six types of land use (Annual Crops, Perennial Crops, Grazing, Espinal, Dense Espinal and Native Forest); and finally, SQI was interpolated at landscape scale using the soil-adjusted vegetation index (SAVI) as an auxiliary variable. SAVI was selected to represent indirect information on vegetation biomass productivity. The results indicate that most LUCC dynamics were observed in the Espinal woodland, where agriculture and grazing activities have been developed historically. The SQI showed significant SQ deterioration when Native Forests (SQI = 0.82) degrade and are transformed by anthropic interventions like Annual Crops (SQI = 0.27), Perennial Crops (SQI = 0.34) or Grassland (SQI = 0.36). However, a slight improvement in SQ compared to the other land uses was identified in the Dense Espinal (SQI = 0.46). Finally, the quality model at landscape scale showed clear differences in SQI values for all landscape covers.

1. Introduction

LUCC is a representative consequence of the pressure of human development on natural landscapes occurring at different spatial and temporal scales (Conacher and Sala, 1998; Geist and Lambin, 2002; Lambin et al., 2001). Depending on the type and the intensity of LUCC, ecosystems end up reflecting different structures, functions, and dynamics, creating new and complex interactions among the elements vegetation, soil, and nutrients (Adeel et al., 2005). Current landscapes are the result of natural and anthropogenic processes, thus a historical perspective is required to understand the dynamics that led to current conditions (Russell, 1997).

The resulting landscape incorporates physical and biological components (DeFries et al., 2004; Foley et al., 2005), reflecting changes in soil properties and consequently in biodiversity and vegetation productivity (Matson et al., 1997; Tscharntke et al., 2005). Several studies have demonstrated the close relationship between LUCC, soil properties and vegetation productivity in different systems (Dörner et al., 2010; Sharma et al., 2011; García-Orenes et al., 2013). In agroforestry systems, most of the land use conversion moves between grassland, new crops, forest substitution, and crop abandonment (Etter et al., 2006; Kastner et al., 2014). In many cases, the consequences of poor agricultural management practices have led to severe degradation that impairs natural functions, mainly regarding soil fertility, and productivity (Kang and Jou, 1986; Niel et al., 2004; Nardi et al., 1996; Zornoza et al., 2007).

The effects of LUCC on soil erosion and vegetation coverage are a common problem in several agroecosystems in Mediterranean regions (Conacher and Sala, 1998; Geri et al., 2010). The Chilean Mediterranean region is recognized as a critical biodiversity spot in the southern hemisphere (Myers et al., 2000). It is also the most important agricultural zone in the country, where most of the population is located (Schulz et al., 2011). This region has historically been subject to intensive land use, mainly by overgrazing and overexploitation, resulting in high levels of erosion and loss in agricultural productivity (Ovalle et al., 1999). Between 1975 and 2008 changes from forest to agricultural land, timber plantations and urban areas were reported, with annual average growth rates of 1.1%, 2.7% and 3.2%, respectively (Schulz et al., 2010).

To understand historical LUCC trends and effects on ecosystems, it is necessary to correlate the different land use (Otto et al., 2007; Symeonakis et al., 2007), and their possible impacts on biomass productivity and SQ in agroforestry ecosystems (Andrews et al., 2002b; Glover...
et al., 2000; Raiesi, 2007). Biomass productivity is an important variable to evaluate ecosystem functionality and health (Whittaker and Likens, 1997). It reflects the amount of energy available to be transferred through vegetation throughout the ecosystem (Gaston, 2000; Erb et al., 2009; Kay et al., 1999). Land use change and soil degradation reduce biomass productivity, influencing biodiversity and the general state of the ecosystem (Erb et al., 2009).

There is a close relationship between vegetation biomass and soil quality (Paz-Kagan et al., 2014). However, the perception of what constitutes good soil varies depending on priorities with respect to soil function (Armenise et al., 2013; Zornoza et al., 2008). Doran and Parkin (1994) defined soil quality as the capacity of specific soils to sustain biological productivity and generate the bases for ecosystem health. One of the most commonly used techniques to quantitatively assess SQ is to transform and assign weights to soil indicators, and their combination in an index (Andrews and Carroll, 2001; Bastida et al., 2006; Karlen et al., 1994; Zornoza et al., 2007). Several local studies of Mediterranean systems show that poor soil quality due to poor management has resulted in degraded natural (Bastida et al., 2006; Trasar-Cepeda et al., 1998; Zornoza et al., 2007) or productive systems (Armenise et al., 2013; Imaz et al., 2010).

In a Mediterranean landscape, the current ecosystem function is a consequence of historical connections of all the elements that are part of the landscape. These connections are rarely considered in soil quality models that focus on specific soil parameters (Paz-Kagan et al., 2014). Nevertheless, the inclusion of additional ecosystem functions in models can be a useful way to improve soil quality interpretation (Herrick, 2000). Some studies have attributed the degradation of the vegetation cover in the Mediterranean area of central Chile to LUCC (Balduzzi et al., 1982; Fuentes et al., 1989), land use pressures (Ovalle et al., 1996b) and the changing dynamics in land cover (Schulz et al., 2010). However, to improve our understanding of the effects of land use change, it is necessary to integrate specific SQ models with vegetation productivity and the current landscape. The objective of this study was to determine the impact of historical LUCC on SQ for typical Mediterranean landscapes, using vegetation biomass productivity as a specific function in a vegetation gradient with different levels of human disturbance over 36 years. The study, which considered a Mediterranean landscape in the Valparaiso Region, Chile, was developed in three steps: 1) definition of historical LUCC trends between 1975 and 2011, 2) development and implementation of a SQI, and 3) proposal of a SQ model based on vegetation productivity at a landscape scale.

### Table 1
Average values of the main soil properties in the studied sites.

<table>
<thead>
<tr>
<th></th>
<th>AC</th>
<th>PC</th>
<th>GR</th>
<th>DE</th>
<th>ES</th>
<th>NF</th>
</tr>
</thead>
<tbody>
<tr>
<td>pH</td>
<td>6.9 ± 0.8</td>
<td>6.2 ± 0.4</td>
<td>5.8 ± 0.1</td>
<td>5.9 ± 0.1</td>
<td>6.6 ± 0.8</td>
<td>5.7 ± 0.3</td>
</tr>
<tr>
<td>TC (%)</td>
<td>1.59 ± 0.44</td>
<td>1.22 ± 0.21</td>
<td>5.8 ± 0.1</td>
<td>5.9 ± 0.1</td>
<td>6.6 ± 0.8</td>
<td>5.7 ± 0.3</td>
</tr>
<tr>
<td>TN (%)</td>
<td>0.11 ± 0.03</td>
<td>0.08 ± 0.02</td>
<td>0.08 ± 0.02</td>
<td>0.10 ± 0.02</td>
<td>0.10 ± 0.06</td>
<td>0.19 ± 0.04</td>
</tr>
<tr>
<td>AP (mg/kg)</td>
<td>68.18 ± 47.07</td>
<td>13.95 ± 5.74</td>
<td>11.60 ± 3.14</td>
<td>22.73 ± 6.95</td>
<td>8.92 ± 2.22</td>
<td>8.75 ± 3.00</td>
</tr>
<tr>
<td>OM (%)</td>
<td>2.93 ± 0.45</td>
<td>2.51 ± 0.25</td>
<td>2.58 ± 0.38</td>
<td>3.08 ± 0.38</td>
<td>2.73 ± 0.91</td>
<td>5.18 ± 1.00</td>
</tr>
<tr>
<td>SR (g h⁻¹ m⁻²)</td>
<td>0.38 ± 0.20</td>
<td>0.31 ± 0.12</td>
<td>0.23 ± 0.06</td>
<td>0.43 ± 0.09</td>
<td>0.26 ± 0.05</td>
<td>0.61 ± 0.15</td>
</tr>
<tr>
<td>BD (g cm⁻³)</td>
<td>1.20 ± 0.11</td>
<td>1.12 ± 0.12</td>
<td>1.39 ± 0.08</td>
<td>1.35 ± 0.13</td>
<td>1.22 ± 0.10</td>
<td>0.95 ± 0.13</td>
</tr>
<tr>
<td>WSA (%)</td>
<td>0.17 ± 0.21</td>
<td>0.10 ± 0.07</td>
<td>0.13 ± 0.07</td>
<td>0.11 ± 0.04</td>
<td>0.15 ± 0.07</td>
<td>0.45 ± 0.10</td>
</tr>
<tr>
<td>Clay (%)</td>
<td>25.3 ± 4.2</td>
<td>23.3 ± 3.7</td>
<td>21.8 ± 2.7</td>
<td>26 ± 6.5</td>
<td>25 ± 5.9</td>
<td>27.5 ± 4.8</td>
</tr>
<tr>
<td>Silt (%)</td>
<td>33.8 ± 4.0</td>
<td>35.9 ± 4.1</td>
<td>39.8 ± 2.5</td>
<td>43.5 ± 13.8</td>
<td>39.9 ± 7.1</td>
<td>39.3 ± 7.4</td>
</tr>
<tr>
<td>Sand (%)</td>
<td>40.8 ± 7.2</td>
<td>39.3 ± 6.9</td>
<td>38.5 ± 3.3</td>
<td>30.5 ± 19.9</td>
<td>35.3 ± 12.7</td>
<td>33.3 ± 11.7</td>
</tr>
</tbody>
</table>

2. Materials and methods

2.1. Study area

The study was conducted in the Mediterranean area of central Chile, specifically in the town of Catapilco (32° 43′6″ S–71° 16′31″ W), Valparaíso Region (Fig. 1), which is at altitudes between 80 and 650 m.a.s.l. and covers an area of approximately 10,000 ha. The average annual temperature is 15.4 °C, the warmest month being January, with a maximum average temperature of 27.6 °C, and the coldest month being July, with a minimum average temperature of 5.4 °C. Average annual precipitation is 547.8 mm, distributed mainly between May and August, with a prolonged dry season of six months between October and March. According to the national soil survey (CIREN, 2003) and the USDA soil taxonomy system, the predominant soil orders in the area are Alfisols, followed by Mollisols and Entisols. In general soils in the study area are highly degraded. Table 1 shows the main characteristics of the assessed soils.

The study area is characterized by the presence of Espinal Acacia caven, the typical Mediterranean landscape of central Chile. This area has historically been affected by farming and intensive livestock grazing (Ovalle et al., 1999). Currently, the main land uses are agriculture, with either Annual Crops (i.e. vegetables and cereals) or Perennial Fruit (i.e. olive trees and vines), cattle and sheep grazing, native forest, scrub and less common, forest plantations (i.e. Pinus radiata and Eucalyptus globulus).

2.2. Land use and land cover change (LUCC)

In order to determine historical trends of the different land covers and land uses, along with establishing the degree of change over the last 36 years (1975–2011), four Landsat images were used: one MSS image from 1975 and three TM5 images from 1992, 2001 and 2011. All the images were geometrically, atmospherically and topographically corrected. Supervised classification was defined by the statistical decision criterion of maximum likelihood (Chuvieco, 2002), using aerial photographs from the same years and high-resolution Google Earth images as references. Image classification details and accuracy assessment measurements for these four images can be found in Hernández et al. (2015). Four maps were developed from this process with the following cover and land use types: Native Forest, Shrubland, Dense Espinal, Espinal, Grassland, Agricultural, Water, Bare Soil and Plantation (Table 2). All the sites were georeferenced with GPS and their locations included on the maps. For each site, the current land use/cover was registered based on field observations on 2011 map. The land use maps from 1975, 1992 and 2001 were made using the same selected points (Table 3). The maps were prepared using ArcMap 10 software (ESRI, Redlands, Calif.).

2.3. Soil characterization based on land use and land cover

Soil sampling sites were selected based on prior knowledge of the area and considering landscape variability based on topography, slope, elevation, soil series and texture. In order to evaluate and compare different soil quality under a gradient of historical land uses we selected the following cover/uses for soil sampling: 1) Annual crops, 2) Perennial Crops, 3) Grassland, 4) Espinal 5) Dense Espinal, and 6) Native Forest (reference soil) (Table 2: Fig 1). Plantation, Shrubland, Water and Bare Soil were excluded from the sampling given that: 1) Plantations and Shrubland covered a small portion of the study area, and 2) Water and Bare Soil were not appropriate for establishing a SQI. Reference soils are normally required for the construction of soil quality models. Native Forest soil was used because it develops freely and reaches a balance in its properties, resulting in long-term stability in its natural ecosystems (Fedoroff, 1987; Gil-Sotres et al., 2005).

Eight replicates sites for each land use were selected to obtain good landscape representation, resulting in a total of 48 soil-sampling sites (Fig. 1). Soil sampling was conducted in June 2012, to a depth of 20 cm at 15 random points at each site. Once in the laboratory, the 15 samples were composited for each site, air dried, and passed through a 2-mm mesh sieve before soil analysis. The following selected chemical, physical and biological properties, commonly used for soil quality models, were determined: pH was measured in deionized water (1:2.5 soil/water) (Zornoza et al., 2007); total C (TC) and total N (TN) were determined by combustion in a Carlo Erba NA 2500 elemental analyzer (Robertson et al., 1999); available P (AP) was extracted using the calcium-acetate-lactate method (Steubing and Fangmeier, 1992). Organic matter (OM) was determined by oxidation with a mixture of dichromate and sulfuric acid, and measured colorimetrically (Schulte, 1995). Bulk density (BD) was calculated by the core method (Blake and Hartge, 1986), with four samples per plot. The water-stability of aggregates (WSA) was determined based on prior knowledge of the area and considering landscape variability based on topography, slope, elevation, soil series and texture. In order to evaluate and compare different soil quality under a gradient of historical land uses we selected the following cover/uses for soil sampling: 1) Annual crops, 2) Perennial Crops, 3) Grassland, 4) Espinal 5) Dense Espinal, and 6) Native Forest (reference soil) (Table 2: Fig 1). Plantation, Shrubland, Water and Bare Soil were excluded from the sampling given that: 1) Plantations and Shrubland covered a small portion of the study area, and 2) Water and Bare Soil were not appropriate for establishing a SQI. Reference soils are normally required for the construction of soil quality models. Native Forest soil was used because it develops freely and reaches a balance in its properties, resulting in long-term stability in its natural ecosystems (Fedroff, 1987; Gil-Sotres et al., 2005).

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Table 2
Description of map classes regarding land use and their relationship to sampling sites.

<table>
<thead>
<tr>
<th>Map class</th>
<th>Sampled cover</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Native Forest</td>
<td>Native Forest</td>
<td>Reference soil. Advanced succession stage of the sclerophyll forest, with species such as: Cryptocarya alba, Peumus boldus, Quillaja saponaria, Lithrea caustica, among others. These natural soils have not been recently altered by human intervention (&gt;40 years). 80–98% woody cover.</td>
</tr>
<tr>
<td>Shrubland</td>
<td>Not sampled</td>
<td>Intermediate situation between the matorral and the sclerophyll forest; cover by arborescent species such as: Acacia caven, Maytenus boaria, Prosopis chilensis, Trevoa trinervis, Colliguaja odorifera and second-growth sclerophyll species. 35–75% woody cover.</td>
</tr>
<tr>
<td>Dense Espinal</td>
<td>Dense Espinal</td>
<td>Thick Acacia caven cover in arborial stage, together with second-growth Quillaja saponaria. In the past, it was used (&gt;20 years) for grazing and rainfed agriculture.51–80% woody cover.</td>
</tr>
<tr>
<td>Espinal</td>
<td>Espinal</td>
<td>Cover showing high density of shrubby Acacia caven, Trevoa trinervis and herbaceous cover. It is sporadically used for livestock rotation and in the past (&gt;10 years), it was used for rainfed agriculture. 26–50% woody cover.</td>
</tr>
<tr>
<td>Grassland</td>
<td>Grassland</td>
<td>Herbaceous cover with isolated Acacia caven and Trevoa trinervis shrubs, 0–10% woody cover</td>
</tr>
<tr>
<td>Agriculture</td>
<td>Annual Crop</td>
<td>Rainfed and irrigated agriculture. 6%–75% woody cover.</td>
</tr>
<tr>
<td>Perennial crop</td>
<td></td>
<td>Olive tree cultivation between 6 and 8 years old.</td>
</tr>
<tr>
<td>Barren Land</td>
<td>Not sampled</td>
<td>Urban areas, rocks, barren lake beds, recently cleared lands, roads, highways</td>
</tr>
<tr>
<td>Water</td>
<td>Not sampled</td>
<td>Rivers, lakes, water reservoirs.</td>
</tr>
<tr>
<td>Plantation</td>
<td>Not sampled</td>
<td>Ornamental trees and plantations of Pinus radiata and Eucalyptus globulus</td>
</tr>
</tbody>
</table>
2.4. Development of the Soil Quality Index (SQI)

The first step to evaluate SQ was to determine the ecosystem function of interest (Armenise et al., 2013). The vegetation biomass productivity function (natural and anthropogenic) was selected because it is measurable at the two levels of interest (site and landscape).

SQI was developed following the general approach of Andrews et al. (2002a), which consists of three main steps: 1) selection of indicators for a minimum data set (MDS), 2) transformation and weighting of MDS indicators, and 3) integration of indicator scores into an index.

The MDS met the conditions set by Burger and Kelting (1999); Doran and Parkin (1996) and Etchevers et al. (2009), which are as follows: 1) easy to measure, 2) measures changes in soil functions, 3) includes physical, chemical and biological soil indicators 4) is accessible to evaluators and applicable in field conditions, and 5) is sensitive to climatic and management variations. Selected MDS indicators were defined considering 1) expert opinion, 2) consensus of regional researchers following Andrews et al. (2002a), and the protocol of Andrews et al. (2003), and 3) recommendations from SQ studies in Mediterranean ecosystems (Armenise et al., 2013; Bastida et al., 2006; Marziali et al., 2010; Zornoza et al., 2007). The final set of MDS indicators included soil pH, TC, TN, AP, BD, WSA, OM and SR. Pearson correlation coefficients were computed to understand the relationships among the selected indicators (Fig. 3).

Subsequently, a factorial analysis with rotated axes was used to estimate the weights of the indicators of the MDS, using a correlation matrix to avoid the effect of the measurement units on the final weights (Bastida et al., 2006; James and McCulloch, 1990). To reinforce the usefulness of the factors selected, the parallel test, a method based on generating random variables by simulation, was applied to determine the number of selected factors (Glorfeld, 1995). The final weights applied to the indicators were obtained from the MDS weighted communalities normalized by dividing by their sum (Table 4) (as it is exemplified using the WSA indicator). The weighted communalities correspond to the sum of the square of the product between each factor loading and the corresponding weighted proportion (Andrews et al., 2002a) (Table 4).

In order to integrate the final weights to form the index, scoring functions of the MDS indicators were then generated. Due to the variability of the absolute values of the indicators, the values were standardized between 0 and 1. The scoring functions were based on the methodology proposed by Andrews et al. (2003). The X axis for these functions represented a specific site range based on the inherent properties of soils or factors of soil formation (Andrews et al., 2003). The Y axis varied from 0 to 1 and provided the transformed score. It is assumed that the expected range for each indicator varies according to a particular site defined by factors such as weather or the inherent properties of soil (Andrews et al., 2004). Consequently, these values were set based on the soil reference values (Native Forest) and literature on Mediterranean systems (Bustamante et al., 1995; Rodríguez et al., 2001). The general forms of the functions are: “more is better” (upper asymptotic sigmoid curve), “less is better” (lower asymptotic sigmoid curve), and having a “midpoint optimum” (Gaussian function) (Andrews et al., 2002a; Karlen and Stott, 1994). The upper function, more is better, was used for soil OM, TC and WSA based on their role in soil fertility, water distribution and structural stability (Andrews et al., 2003; Tiessen et al., 1994). It was also used for soil TN to determine appropriate nutritional levels and ecologically reasonable levels of nitrogen in the soil (Glover et al., 2000), and for SR due to its key role in the dynamics of soil OM (Marziali et al., 2010; Needleman et al., 1999). To normalize the tendency, an equation that defines a sigmoidal curve (Eq. (1)) was used, with an asymptote that tends to 0 and another that tends to 0. The function of less is better (Eq. (1)) was used for BD because at high values it has an inhibitory effect on plant root growth due to its effect on soil porosity (Andrews et al., 2003; Grossman et al., 2001). The optimum or Gaussian function (Eq. (2)) was used for pH based on the effects on nutrient availability (Andrews et al., 2004; Smith and Doran, 1996). It was also used for soil AP based on crop response and environmental hazard (Andrews et al., 2003; Maynard, 1997).

\[
y_{ij} = \frac{1}{1 + (x_{ij} - a_j - b_j)^2}
\]

(1)

\[
y_{ij} = \frac{1}{1 + z_j(x_{ij} - a_j)^2}
\]

(2)

where: \(y_{ij}\) is the value of each observation \(i\) in the \(j\) indicator obtained from the membership function; \(x_{ij}\) is the measured value (field/laboratory) of each observation of the \(j\) indicator; \(a_j\) is the median observation

Table 3

<table>
<thead>
<tr>
<th></th>
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</tr>
</thead>
<tbody>
<tr>
<td>GR (50%)</td>
<td>AC (100%)</td>
<td>AC (100%)</td>
<td>AC (100%)</td>
<td></td>
</tr>
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<tr>
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<td>AC (12.5%)</td>
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<tr>
<td>GR (25%)</td>
<td>AC (12.5%)</td>
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<tr>
<td>ES (25%)</td>
<td>AC (12.5%)</td>
<td>AC (12.5%)</td>
<td>AC (12.5%)</td>
<td></td>
</tr>
<tr>
<td>NF (25%)</td>
<td>NF (25%)</td>
<td>NF (25%)</td>
<td>NF (25%)</td>
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<tr>
<td>SH (100%)</td>
<td>NF (25%)</td>
<td>NF (25%)</td>
<td>NF (25%)</td>
<td></td>
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</tbody>
</table>


Table 4

<table>
<thead>
<tr>
<th>Indicator</th>
<th>Factor 1</th>
<th>Factor 2</th>
<th>Factor 3</th>
<th>Weighted communality</th>
<th>Final weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>WSA</td>
<td>0.49</td>
<td>0.01</td>
<td>0.87</td>
<td>0.11</td>
<td>0.08</td>
</tr>
<tr>
<td>TC</td>
<td>0.87</td>
<td>-0.05</td>
<td>0.30</td>
<td>0.25</td>
<td>0.19</td>
</tr>
<tr>
<td>BD</td>
<td>-0.65</td>
<td>-0.11</td>
<td>-0.41</td>
<td>0.15</td>
<td>0.11</td>
</tr>
<tr>
<td>OM</td>
<td>0.94</td>
<td>-0.11</td>
<td>0.18</td>
<td>0.30</td>
<td>0.23</td>
</tr>
<tr>
<td>TN</td>
<td>0.97</td>
<td>0.05</td>
<td>0.17</td>
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<td>0.24</td>
</tr>
<tr>
<td>AP</td>
<td>-0.01</td>
<td>0.01</td>
<td>0.06</td>
<td>0.12</td>
<td>0.09</td>
</tr>
<tr>
<td>pH</td>
<td>-0.03</td>
<td>0.99</td>
<td>-0.13</td>
<td>0.05</td>
<td>0.04</td>
</tr>
<tr>
<td>SR</td>
<td>0.58</td>
<td>-0.02</td>
<td>0.36</td>
<td>0.12</td>
<td>0.09</td>
</tr>
<tr>
<td>SS Loadings</td>
<td>3.58</td>
<td>1.38</td>
<td>1.23</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Proportiona</td>
<td>0.45</td>
<td>0.17</td>
<td></td>
<td>0.15</td>
<td></td>
</tr>
<tr>
<td>Weighted proportionc</td>
<td>0.58</td>
<td>0.22</td>
<td>0.20</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

a Quadratic sum of the loads for each factor.
b Proportion of total variance explained by each factor.
c The weighted proportion corresponds to the value of the proportion explained by each factor divided by the sum of all proportions. e.g. for factor 1: 0.45 * (0.45 + 0.17 + 0.15)^-1 = 0.58.
taken for each $j$ indicator; $z_j$ is the maximum value among the $j$ indicator value; regarding $k = 1$ (more is better), $b_{jk}$ corresponds to $z_j - a_j$ for each $j$ indicator; regarding $k = 2$ (lower is better), $b_{jk}$ corresponds to the difference between $a_j$ and the minimum value of the field/laboratory measured data for each $j$ indicator.

The normalized scores of the MDS indicators were obtained using the scoring functions, and the final weights derived from factor analysis. They were then integrated into a standardized weighted-additive index between 0 and 1 (Eq. (3)):

$$SQI = \sum_{j=1}^{k} w_j y_j$$  \hspace{1cm} (3)

where $SQI$ is the soil quality index value, $k$ is the number of indicators that make up the MDS, in this case, $k = 8$; $w_j$ is the final weight assigned to each indicator, and $y_j$ is the score for each $j$ indicator. Tukey’s HSD multiple comparison test ($p < 0.05$) was applied to identify differences between $SQI$ and different land uses.

Statistical analysis was performed in R software.

2.5. Evaluation of soil quality at the landscape scale

To validate the relationship of the $SQI$ to the function of vegetation biomass productivity, a remote sensing tool was applied to extrapolate soil quality and biomass productivity results at the landscape scale. $SAVI$ was selected (Huete, 1988) to measure vegetation greenness (relative biomass), which can be linked to either high or low SQ and productivity of vegetation biomass. This index uses the contrast of the characteristics of two bands in a multispectral raster dataset: chlorophyll pigment absorptions in the red band ($R$) and the high reflection capability of vegetation in the near-infrared band ($NIR$).

$$SAVI = \frac{NIR - R}{NIR + R + L} \times (1 + L)$$  \hspace{1cm} (4)

where $SAVI$ is the vegetation index value, which varies between $-1$ and $1$; $L$ varies depending on vegetation cover (Table 2), assigning a value of 0 to areas with high vegetation cover and 1 to areas without vegetation.

To estimate $L$ values, richness, abundance and density of vegetation obtained in the study area were used through vegetation characterization. $L$ values were established as follows: Bare Soil and Water $L = 1$, Grassland $L = 0.7$, Agriculture $L = 0.5$, Espinal $L = 0.3$, Shrubland $L = 0.2$, Dense Espinal $L = 0.1$, and Plantation and Native Forest $L = 0$. This correction factor was applied to all classes obtained from the 2011 land use map, as the goal was to have a SQ monitoring mechanism at a landscape scale and not just for land uses evaluated with $SQI$. With this goal in mind, and considering that $SAVI$ is a continuous representation of the landscape vegetation, $SQI$ values were correlated with $SAVI$ values by a Pearson correlation coefficient, taking into consideration that the points overlap in both cases (Fig. 5).

From this analysis, a SQ model was created for the landscape of interest (Fig. 7). The spatial data were interpolated using geostatistical...
analysis to estimate SQI values in unsampled locations. We used the
cokriging technique from the cross-correlation between the SQI and
SAVI. A cross-variogram was determined to calculate the degree of spa-
tial variability among neighboring observations for each variable. The
cross-variogram function was calculated as follows (Eq. (5)):

\[
\gamma_{12}(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} [Z_1(X_i) - Z_1(X_i + h)] [Z_2(X_i) - Z_2(X_i + h)]
\]

where \(N(h)\) is the number of pairs of experimental observations and \(Z(x_i), Z(x_i + h)\), separated by an \(h\) vector, and \(Z_1\) and \(Z_2\) are spatially cor-
related variables. In fitting the theoretical model to experimental
variograms, the coefficients, nugget effect (\(C_0\)), sill (\(C_0 + C_1\)), structural
variance (\(C_1\)) and range (\(a\)) were determined. The model tested for
fitting was spherical. The model was chosen based on ordinary least
squares.

Geostatistical analyses, as well as the interpolations, were performed
using GS + software for Windows, version 9.1 and the geostatistics
module of ArcMap 10 software (ESRI, Redlands, Ca.).

3. Results and discussion

3.1. Historical trends of land cover and land use change

As a result of the historical LUCC trends presented throughout the
study period (1975–2011), the spatial distribution of different covers
was configured in the landscape and the persistence of changes present-
ed on the various landscape covers was identified (Fig. 2). We found
that only 4% of the area did not suffer any LUCCs, while 19% suffered
one change, 42% two changes, and 35% three changes (Fig. 2).

The most intense changes occurred in the Espinal, with rotation be-
tween grazing and rainfed crops, mainly between 1975 and 1992
(Table 3). Later (1992–2001) rainfed crops were abandoned, grazing
remained in several areas, even to the present day, and in other areas
cattle raising had discontinued (Table 3). This dynamic has allowed
for the regrowth and increase of Espinal A. caven in some areas, forming
a Dense Espinal cover in the last period (2001–2011; Table 3). In the
steepest areas, the main changes consisted of converting Native Forest
to Shrubland (Table 3). Land use for Annual Crops was more stable,
showing just one change throughout the study period (Table 3). Peren-
nial Crops are introduced recently, so these soils have been subjected to
two and three changes, mainly from Grassland to Espinal (Table 3).
Schulz et al. (2010) studied the entire Mediterranean region of central
Chile, and found a similar tendency for changes among grassland,
espinal forest, and agriculture land. Changes from degraded or aban-
donated land to forest were less common.

3.2. Comparative assessment of SQ among different land uses/covers

Factor analysis showed that three factors explained 77% of the vari-
ance of the MDS indicators (Table 4). With the first factor, chemical (TN,
TC, OM), biological (SR) and physical (BD) indicators showed the
highest loadings due to their high correlation (Fig. 3). Factor 2 showed
a clear separation of chemical indicators (pH and AP), and factor 3
showed a clear separation of physical indicators (WSA) (Table 4).
Additionally, the final weight assigned to the MDS indicators signi-
ficantly pondered the indicators OM, TC and TN (Table 4). Furthermore,
the remaining indicators made a low contribution to explaining the
total variability in the factorial model due to a lower correlation with
the other indicators (Table 4, Fig. 3).

The final weights assigned to each MDS indicator were integrated
into a SQI ranging from 0 to 1. The results from the application of the
SQI showed a clear separation of SQ in the different studied land uses.

As expected, the comparison of SQ among the different land uses
showed that the SQI in Native Forest soils presented the best SQ
(SQI = 0.82), which is significantly different (p < 0.05, Tukey HSD)
from those of the other uses (Fig. 4). This was mainly due to the high in-
dividual contribution of WSA, TC, OM, TN and pH (Fig. 4). Islam and
Weil (2000) tested a degradation index in which farming soils showed
much higher degrees of degradation than soils with natural covers.
Similarly, Marzaioli et al. (2010) applied a SQI to different land uses in
Mediterranean Italy, and found that coniferous and broadleaf forests

Fig. 3. Pearson correlation coefficients for different soil properties, with a level of significance \(\alpha = 0.05\). Histograms and trends for each indicator are shown. The asterisk (*) indicates a
statistical difference from zero.
have a superior quality than scrubland and grassland, the latter two having intermediate values, and than perennial crops, which presented the lowest SQ values. This can be attributed to the fact that Native Forest soils had the least human intervention during the study period (Table 3).

Dense Espinal soils showed an intermediate SQ value (SQI = 0.46) relative to the other land uses (Fig. 4). This may be due to the LUCC history of these soils (Table 3), which were used extensively between 1975 and 1992, with rotation between grazing and rainfed crops, before the land was abandoned. Hernández et al. (2015) suggested that land abandonment resulted in increased shrubland and tree density, mainly A. caven, along with an increase in herbaceous vegetation and recolonization of some typical native forest species (e.g. Quillaja saponaria). This dynamic probably produced a gradual improvement in soil properties, suggesting a SQ recovery. Applying an SQI, Marziali et al. (2010) found that SQI recovered to a level comparable to the quality of undisturbed soils in scrublands with the presence of a herbaceous layer and other wild plants. Using two distinct SQIs, Zornoza et al. (2008) found that abandoned agricultural soils in the Mediterranean area showed less variability in relation to soils in less disturbed forest than soils under almond production. Sánchez-Marañón et al. (2002) also observed a slow recovery of soil physical and chemical properties in abandoned cereal croplands in southern Spain. Similarly, studies in the Mediterranean basin have found that the regeneration of natural vegetation, often after land abandonment, decreases soil erosion (Grove and Rackham, 2001). A similar situation may be occurring in the Dense Espinal soils, as vegetation cover is an important requirement to improve OM content, soil structure and the infiltration rate, protecting soils from erosion (Kosmas et al., 2000; Trimble, 1990), and therefore improving SQ. Similarly, Caravaca et al. (2003) suggested that shrubs and perennial grasses improved SQ in an abandoned Spanish Mediterranean agro-ecosystem by increasing soil OM and soil nitrogen content, as well as favoring the formation of stable aggregates and developing propagules. Contrarily, Pascual et al. (2000) found that the abandonment of agricultural soils in semi-arid Mediterranean Spain produced severe soil degradation, with a decrease in soil OM, soil microbial biomass, basal respiration and soil enzyme activities.

Perennial Crop and Grassland soils showed similar SQs, although weaker than Dense Espinal soils, with SQI values of 0.34 and 0.36, respectively (Fig. 4), which is explained by constant agroforestry rotation of these sites, such as Espinal, grazing pastures and rainfed crops (Table 3). Raiesi (2007) reported that LUCC (conversion of pastures to almond orchards and then to alfalfa fields) negatively influenced properties like bulk density, porosity and aggregate stability, decreasing SQ. Additionally, Perennial Crops, apart from olive trees, do not have cover that protects the soil (e.g. grasses or herbaceous plants), which probably decreases the SQ of these soils (Fig. 4).

Finally, the SQI value of Annual Crop soils was not significantly different from that of Espinal soils, presenting the lowest SQ values, 0.27 and 0.29, respectively, because they have similar individual contributions from the different indicators (Fig. 4). The poor SQ of Annual Crops (Fig. 4) is explained by the permanent use (> 20 years) of these soils for agriculture (Table 3). Applying an SQI, Zornoza et al. (2008) found in undisturbed, agricultural and abandoned agricultural soils, that agricultural practices disrupt the natural balance of the soil. In addition, continuous tillage and fertilization lead to imbalance among soil indicators, accompanied by decreased OM, which has been reported as the main contributor of cultivated soil degradation (Davidson and Ackerman, 1993; Moscatelli et al., 2007; Nardi et al., 1996).

These SQI results show that SQ deteriorates significantly when native forest systems are degraded and transformed to uses such as Annual Crops, Perennial Crops or Grassland. It is also clear that SQ can improve when anthropogenic uses like cultivation or grazing are abandoned and re-vegetation subsequently occurs (Fig. 4).

3.3. SQ Monitoring at the landscape scale

To monitor SQ at a landscape scale, a model was generated from the interpolation of SQI with SAVI. Studies have shown the efficiency of SAVI to measure the productivity of different vegetation covers (Farzadmehr et al., 2004; Hobbs, 1995). This efficiency was related to SQI (Fig. 5), demonstrating that these two indices are suitable for interpolating SQ at landscape scale (Figs. 6, 7). From this relation we adjusted a cross-variogram between SQI and SAVI (Fig 6) with a high degree of spatial dependence (R2 = 0.86) for the observed and the estimated semivariance (nugget = 0.018, sill = 0.029, structural variance = 0.011, range = 772.81). The model showed that the spatial continuity of the interpolated variable (SQI) was enhanced by the inclusion of the continuous spatial variable

![Fig. 4](image-url)  
SQI comparison among different land uses. The different shades of gray show the contribution of each MDS indicator to SQI. Error bars indicate the standard deviation of all values in the index. Significant differences among land uses are identified with different letters after a Tukey HSD test (α = 0.05). AC: Annual Crop, PC: Perennial Crop, GR: Grassland, DE: Dense Espinal, ES: Espinal, and NF: Native Forest.

![Fig. 5](image-url)  
Linear associations between SQI and SAVI for the different sampling points. The coefficient of determination (R2) regarding the relationship among the indicators is shown.
The spatial distribution of sample points is not homogeneous throughout the study area (Fig. 1). Consequently, the application of kriging prediction without the use of an auxiliary variable presented a weak value ($R^2 = 0.56$, exponential model) for the SQI estimation. Previous studies have demonstrated that when the auxiliary variable has greater continuity than the main variable, the resulting cokriging map tends to have this characteristic, contributing to a higher representation of the spatial variability (Silva et al., 2010; Silva and Lima, 2014).

The landscape model allowed us to identify the spatial distribution of the differences in SQ throughout the study area and helped identify a SQ gradient among different vegetation covers (Fig. 7). The high correlation between SAVI and SQI (Figs. 5, 6) helped to generate a more accurate spatial extrapolation among the measurement points performed on land (Cyr et al., 1995; Silva et al., 2010).

This made it possible to determine that the main SQ fluctuations occurred in the Espinal valleys (light blue to yellow in Fig. 7). This area has the largest Espinal distribution at different densities (i.e. Espinal, Dense Espinal and Grassland). The variation in SQ is the result of the historical land use that these Espinals have undergone (Fig. 2, Table 3). This trend is reflected in the whole Mediterranean area of central Chile, where the intense use of land by overgrazing and over-harvesting has dramatically depleted soil nutrients and damaged primary and secondary productivity, as well as biodiversity (Ovalle et al., 1999). This is because Espinals are compatible with most of the Chilean Mediterranean livestock industry and rainfed cereal production areas (Ovalle et al., 1990; Ovalle et al., 1996a), which are normally present in small locations (2 to 20 ha) and within a heterogeneous landscape dominated by different levels of coverage of *A. caven* (Muñoz et al., 2007). Espinal ecosystems are more degraded on slopes where pasture-crop rotation has been intense, (blue tones in Fig. 7) and with less *A. caven* coverage. Therefore, more erosion and soil nutrient depletion are observed (Muñoz et al., 2007). In contrast, on plains where land use has been less intense and where rainfed crops have been discontinued, *A. caven* cover is more intense and some typical species of native forest have established themselves (e.g. *Q. saponaria*), allowing Dense Espinal development in the last 10 years (Table 3). This dynamic resulted in an SQ improvement in the landscape model (in yellow in Fig. 7). Ovalle et al. (1996a) found that discontinuation of grazing and crop production resulted in further development of *A. caven* coverage, resulting in better soil conservation. This evidence demonstrates that SQ can gradually improve even after the soil has been subjected...
to intensive use for several years. Ovalle and Godron (1989) stated that A. caven in espinal cover seems to favor patch growth as a consequence of more favorable conditions under tree canopies, where productive herbaceous species are concentrated. This improvement in vegetation also boosts soil properties, leading to improved SQ. Finally, better SQ was observed in the higher elevations of the landscape, where most Native Forest is distributed (brown in Fig. 7), which is because there is less human intervention and better plant succession (scrubland to forest) during the period under study (Table 3).

SQ is essential to maintain good vegetation cover and vice versa. These elements must be carefully considered in the landscape mosaic when planning to maintain and regulate habitat and landscape functions.

4. Conclusions

The results of this study demonstrate the efficiency of SQ in assessing SQ for different land uses. In addition, they provided important evidence about the effect of the LUCC dynamic on SQ. The SQ results showed that there was a significant SQ deterioration when Native Forest systems degrade and are transformed for anthropic uses like Annual Crops, Perennial Crops or Grassland.

In addition, we found that SQ gradually recovers in areas that were used for grassland and crops and then abandoned (e.g. Dense Espinal). Based on this, we can say that: 1) except for Native Forest, the evaluated covers decrease the capacity for vegetation productivity, and 2) soil capacity for vegetation productivity improves when land is abandoned and subsequent revegetation takes place.

The results also demonstrate the advantages of using spectral data along with modeling field data to identify and evaluate SQ in different land uses at the landscape scale, by identifying a SQ gradient of different landscape covers. The application of spectral data is a good tool to improve the interpolation of SQ. SAVI was a good auxiliary variable to improve the interpolation of SQI. SAVI was a good auxiliary variable to determine which land uses are most suitable for a given area. The parameters selected in this study to demonstrate the efficiency of SQ can be analyzed and modified according to the function to be evaluated.

In general, by understanding SQ at a site level we can associate basic ecosystem functions like total vegetation biomass. However, maintaining good ecosystem quality based on total vegetation biomass without recognizing the reality of managing land for other uses is too simplistic.

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Appendix A. Supplementary data

Supplementary data related to this article can be found in the online version, at http://dx.doi.org/10.1016/j.catena.2016.01.029. These data include the Google map of the most important areas described in this article.

References


