Vol. 78: 261–270, 2019
https://doi.org/10.3354/cr01574

CLIMATE RESEARCH
Clim Res

Published online October 17

Effect of climate data uncertainty on ecological land classification: a case study from Argentina

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ABSTRACT: Ecological studies based on gridded climate data are increasingly common, but the effect of the uncertainty of climate data on ecological estimations is rarely assessed. Here, we assessed the effect of the uncertainty of local and global climate data (LCD and GCD, respectively) on ecological land classifications, using the Holdridge life zones and the country of Argentina as a case study. We quantified the uncertainty in LCD using information from meteorological stations and a simulation approach, which allowed us to create an altered LCD (aLCD), and to quantify the agreement between LCD and aLCD through confidence limits. Then, we quantified the agreement between the life zone maps derived from GCD and LCD — while accounting for LCD uncertainties — and assessed the effects of spatial resolution, environmental resolution, and topographic heterogeneity. We found that the mean agreement between LCD and aLCD for the whole country was about 75%, but there were important variations in the amplitude of the confidence intervals depending on the region. In addition, the mean agreement between ecological maps derived from LCD and GCD ranged between 40 and 83%. However, the LCD–GCD agreement fell inside the confidence limits of the LCD, and decreasing the spatial resolution from 1 to 50 km did not change the results. Decreased thematic resolution improved the agreement in the tropical and antiboreal regions. Overall, our study shows that uncertainties in ecological applications of climate data are higher in environmentally heterogeneous lands, and highlights the need for incorporating climate data uncertainties into ecological studies.

KEY WORDS: Agreement · Climate data · Land classification · Holdridge life zones · WorldClim

1. INTRODUCTION

High-resolution, spatially gridded climate data provide vital information in ecological studies (Abatzoglou 2013, Belda et al. 2014, Booth 2018). Gridded climate data are used to assess the impact of climate change on land use (Zak et al. 2008, Yan et al. 2017), for modeling species distributions (Peterson & Nakazawa 2008, Soria-Auza et al. 2010, Pliscoff et al. 2014, Nori et al. 2016), and for assessing biodiversity conservation (Araújo & Rahbek 2006, Bellard et al. 2012, Schirone et al. 2016), among other functions. However, there are important uncertainties in gridded climate data, which can arise from the process of spatial gridding, temporal modeling, or bias in the observed data, for example (Baker et al. 2017). Nevertheless, there are important sources of uncertainty involved in the process of high-resolution spatial gridding or temporal modeling as well as possible bias in the observed data (Baker et al. 2017). Even though gridded climate data are widely applied, little attention has been paid to the effect of such data uncertainty

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on spatially extensive environmental research (Fick & Hijmans 2017). Such effects might not be easy to recognize, and thus, scientists may not be aware of climate data uncertainties (Behnke et al. 2016).

Gridded climate data used in ecological studies come typically from 2 main sources or scales, including local-scale data (i.e. developed for a particular geographic region or country; Haylock et al. 2008, Jones et al. 2009, Bianchi & Cravero 2010), or global-scale data, such as WorldClim (e.g. New et al. 2002, Hijmans et al. 2005, Fick & Hijmans 2017). These data are derived from weather observations, including *in situ* and remotely sensed observations, and are nowadays available at fine spatial resolution (≤1 km), which is ideal for capturing detailed environmental variation across landscapes (Hijmans et al. 2005). While ecological studies for a specific region or country typically use climate data developed for that particular area (i.e. local climate data, LCD), extrapolating the results to other regions or forecasting changes under future scenarios requires the use of global climate data (GCD). Furthermore, understanding the differences between local and global climate data sets is particularly important in the face of climate change because available climate data for future scenarios are typically global (Tapiador et al. 2019). Advancing the use of climate data in ecological studies requires a clear understanding of the uncertainties of LCD versus GCD data sets.

The Holdridge life zones system (Holdridge 1967) allows for ecological land classification based on simple climatic variables (temperature and precipitation), and represents a valuable tool for assessing the uncertainties of LCD and GCD (Metzger et al. 2013, Derguy et al. in press). For studies using LCD (e.g. country level), it is important to evaluate how uncertainties in the local climate data affect the ecological land classification, i.e. the distribution of life zones. Meteorological stations can be used to quantify those uncertainties (Behnke et al. 2016). In contrast, for studies using GCD, it is important to assess the differences between the land classifications derived from GCD versus LCD, including both the magnitude and the spatial variation of those differences. Ideally, the differences between the 2 maps should be statistically small across the landscape, that is, within the range of the uncertainty of the LCD.

At the same time, the comparison between 2 maps can be affected by the spatial resolution, as a case of the 'modifiable areal unit problem' (MAUP; Openshaw 1984). This problem can be investigated by aggregating the pixels to a smaller spatial resolution (i.e. larger pixel sizes; Stillwell et al. 2018). In turn, a trend in map agreement carried out through a range of pixel sizes can be used to find the appropriate spatial resolution for map comparison. However, when categorical maps are compared through pixel-to-pixel agreement, a difference in category label is considered an error even if the correct category can be found in a neighboring pixel, or if it falls into the fringes of different categories but is environmentally similar (Power et al. 2001, Pontius & Suedmeyer 2004). Spatial resolution is a complex issue in modeling climate and its applications (Bedia et al. 2013, Behnke et al. 2016, Karger et al. 2017).

Changes in thematic (environmental) resolution can also affect the estimations of compositional and configurational landscape metrics, which is also considered a form of MAUP (Buyantuyev & Wu 2007). Similar to the problem of spatial resolution, the problem of thematic resolution can be investigated by combining the thematic classes into fewer, broader classes. Furthermore, gridded climate data involve spatial interpolation models, which are usually less reliable in environmentally complex landscapes than in homogeneous ones (Yao et al. 2013). Therefore, mismatches between local and global gridded data are expected to be more frequent in geographical areas with higher topographical heterogeneity than in flat areas. However, there is little information on the effects of topography and environmental resolution on climate-based ecological land classifications.

Our main goal was to assess the effect of the uncertainty of LCD on ecological land classification, and to compare it to ecological maps derived from GCD. Using Argentina as a case study, we aimed to: (1) quantify the effect of the uncertainty of local gridded data on Holdridge life zones in Argentina; (2) assess the agreement between Holdridge life zones in Argentina based on local and global gridded data; (3) assess the effect of spatial and environmental resolutions on the agreement between Holdridge life zones based on local and global gridded data; and (4) evaluate the extent to which the observed agreements are related to climatic and/or topographic heterogeneity.

2. MATERIALS AND METHODS

2.1. Study area

We conducted our study in Argentina (Fig. 1), which occupies an area of 2 790 000 km^2 from 21°46' S at the Province of Jujuy to 55°03' S at Isla Grande of Tierra del Fuego (IGN 2016). Argentina

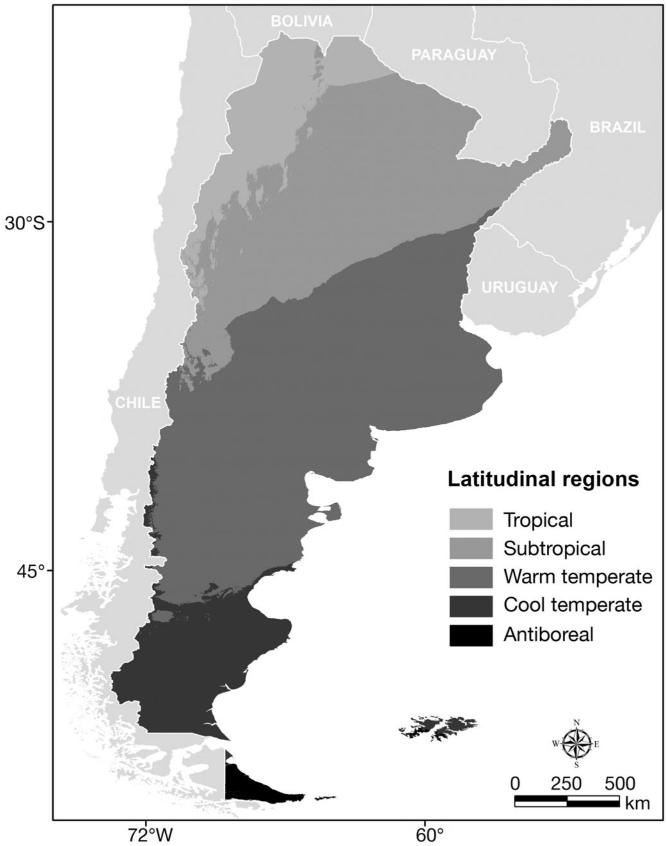

Fig. 1. Latitudinal regions (*sensu* Holdridge) in Argentina. Modified from Derguy et al. (in press)

exhibits a great environmental heterogeneity as a result of wide latitudinal and altitudinal ranges, from −105 m in the Gran Bajo de San Julian to 6961 m a.s.l. in the Aconcagua (Morello & Matteucci 2000). About 65% of the country area is in the eastern lowlands, 25% in the range 500–2000 m a.s.l., and the remainder is in the western mountainous land. Mean annual temperature ranges from 24°C in the north (Formosa Province) to 5–6°C in the south (Tierra del Fuego Province). Mean annual precipitation is about 2000 mm in the northeast (Misiones Province) and diminishes to the west and south, with the exception of some rainy areas farther west, triggered by the eastern flanks of the sub-Andean sierras. The other high precipitation area, including small areas with >2000 mm annual precipitation, is located in the Patagonian Andes (Bianchi & Cravero 2010). Finally, an extensive arid diagonal mainly with <200 mm traverses the country from the northwest (Puna and neighboring lower elevated terrains) to the Patagonian tablelands (Mancini et al. 2005).

2.2. Holdridge life zones

The Holdridge life zones system (Holdridge 1967) was used to assess the effect of the uncertainty of LCD on land classification maps, as well as the agreement between the maps derived from LCD and GCD. The Holdridge life zones system has been used for ecological land classification in countries all over the world (Lugo et al. 1999, Yue et al. 2001, Chakraborty et al. 2013, Tres 2016). According to Holdridge, a life zone is defined by ranges of 3 variables at logarithmic scale, including (i) mean annual biotemperature (BT; mean annual temperature ranges from 0°C to 30°C); (ii) mean annual precipitation (PP); and (iii) potential evapotranspiration ratio (EVP). These variables are known to limit biological processes (Holdridge 1947, 1967). At the same time, the Holdridge life zones system defines 3 broader zoning levels: (i) latitudinal regions, according to heat distribution at sea level (basal biotemperature); (ii) altitudinal belts, according to heat distribution at terrain surface biotemperature, and (iii) humidity provinces, as a function of the potential evapotranspiration ratio (Derguy et al. in press).

For the purpose of this paper, we defined Holdridge life zones based on BT and PP, and focused on the latitudinal regions for the broader zoning levels. Potential evapotranspiration ratio is derived from temperature and precipitation (EVP = [BT×58.93]/PP). The EVP defines the humidity provinces as well as ecotonal or transition zones between the life zones, which must be assigned to the nearest life zone using fuzzy or hard classification (Lugo et al. 1999, Derguy et al. in press). Such a procedure would have complicated the implementation of the randomization method carried out here for simulating the effect of the uncertainty in local climate data on the ecological land classification (explained in methods). The differences between the maps obtained with and without considering EVP were analyzed by M. R. Derguy (unpubl. data), and reveal that the most of the differences were accounted for by the confusion of ecologically very similar life zones, as they were all below 1.5°C mean annual temperature. M. R. Derguy et al. (unpubl. data) also found that — ignoring such confusion — the percent agreement between the maps exceeds 95%. Thus, we defined the Holdridge life zones maps using only mean annual biotemperature and total annual precipitation.

The original names of latitudinal regions as defined by Holdridge (1967) were used in Derguy et al. (in press). In the present work, the boreal region was renamed as 'antiboreal region' as suggested by Tuhkanen (1992).

2.3. Climate data

We used gridded temperature and precipitation data from 2 sources, including one local model (i.e. national) and one global model. For LCD, we used the Digital Climatic Atlas of Argentina (INTA) (Bianchi & Cravero 2010), which is the official climate data developed by the Argentinian government at a spatial resolution of 1 km. For GCD, we used WorldClim (Fick & Hijmans 2017), which provides climatic information at a global scale with a spatial resolution of 1 km (Fick & Hijmans 2017). Additionally, we used mean annual temperature and total annual precipitation data from 80 meteorological stations distributed across the country from the National Weather Service of Argentina.

Although both LCD and GCD were developed from similar raw data, including *in situ* and remotely sensed observations, different procedures were used for spatial interpolation. The LCD were derived from historical local observations made in different time periods between 1921 and 2000. Such data were interpolated using spatial and topographical models, and corrected based on the opinion of local experts (Bianchi & Cravero 2010). The GCD, in contrast, were derived from monthly average climate data from weather stations from a large number of global, regional, national, and local sources, mostly for the 1970–2000 periods. These data were interpolated using the thin-plate smoothing spline algorithm implemented in ANUSPLIN and utilizing satellite-derived data and other covariates — mean monthly cloud cover, and maximum and minimum land surface temperature (Fick & Hijmans 2017). The data from the meteorological stations represent the 1981–2010 period. Because the time periods of different climate data sources (i.e. LCD, GCD, and meteorological stations) overlap, we assumed that the differences between LCD and GCD were a result of different interpolation methods, climate variability, and the effect of the uncertainty in climate data.

2.4. Data analysis

2.4.1. Uncertainty associated with local gridded data

To evaluate the effect of uncertainties in LCD using the Holdridge land classification for Argentina, we conducted a series of steps. First, we calculated the absolute difference in mean annual temperature and total annual precipitation between the LCD and the 80 meteorological stations. Further, we defined the non-outlier range of observed differences between LCD and meteorological stations as −D90 to D90, where D90 was the 90th percentile of the differences. The range of differences was calculated separately for data between 0–300 mm and >300 mm total annual precipitation since differences were clearly greater for greater precipitation values. No such segmentation was needed for mean annual temperature. Then, we altered each value in the LCD by a random value taken from the range of observed differences, resulting in an 'altered' LCD (hereafter, aLCD). After that, we measured the percent agreement in Holdridge life zones calculated from the original LCD and the aLCD. This procedure was carried out 1000 times, and we calculated the mean percent agreement as well as the 5th and 95th percentiles, which were taken as 90% confidence limits for the percent agreement. These confidence limits were then used as a measure of the variability (i.e. uncertainty) in the Holdridge life zones calculated from the LCD given the variability of such climatic data. Specifically, the percent agreement was taken as a simple measure of concordance between maps based on a cell-to-cell comparison. The analyses were conducted in R (R Core Development Team 2007). In the Results, we report the agreement between LCD and aLCD for the whole country and by latitudinal region, to assess geographical variations in such agreement.

2.4.2. Agreement between LCD and GCD compared with the uncertainty of the LCD

We compared the Holdridge life zones maps derived from the LCD and GCD sources, and calculated the percent agreement at the level of the whole country and by latitudinal region. Then, we evaluated whether the percent agreement between models was contained within the confidence intervals estimated for the percent agreement between LCD and aLCD. The assumption is that if the percent agreement between LCD and GCD maps was contained within the uncertainty of the LCD map, then the 2 maps are not statistically significantly different. Otherwise, if the percent agreement between the LCD and GCD maps was outside of the confidence levels of the LCD map, then the 2 maps are statistically significantly different.

2.4.3. Spatial and environmental variability of LCD–GCD agreement

To assess the effect of spatial and environmental resolution on the agreement between Holdridge life zone classification based on LCD and GCD, we used Pontius et al.'s (2004) multiple resolution analysis. We used the VALIDATE module of IDRISI software (Eastman 2012) to calculate the agreement between the 2 maps for a series of spatial resolutions, ranging from 1 to 1000 km. Each spatial resolution was created by aggregating neighboring pixels into an increasingly coarse grid (Pontius 2000, Pontius et al. 2004). The most frequent class among the aggregated pixels was assigned to the new, larger pixel. The comparisons were made at the level of the whole country and by latitudinal region, for each spatial resolution. In particular, 3 variables were used to compare the models (Pontius et al. 2004): (1) total percent agreement: the proportion of grid cells classified correctly, which is the most commonly used measure of agreement between maps (hereafter, percent agreement); (2) chance agreement: the agreement that could be achieved with no information of location and no information of quantity, which is the agreement between the reference and a map that has a membership of 1/*J* to each category in every grid cell, where *J* is the total number of categories; and (3) grid cell agreement: the additional agreement when the comparison map is accurate in terms of its specification of the grid-cell-level location of each category, which is estimated as the difference between the percent agreement and the agreement of a reference map (LCD) and a modified comparison map (GCD) where cells are randomly relocated (Pontius 2000, Pontius et al. 2004).

To test the effect of thematic resolution, we combined adjacent ranges of biotemperature and precipitation from the Holdridge life zones: <1.5–3, 3–12, and 12–30°C for biotemperature, and 0–125, 125–500, 500–2000, and 2000–8000 mm for precipitation. The approach combined 4 life zones into a new category (Fig. 2). Because we used the ranges of biotemperature and precipitation defined by the Holdridge system for separating life zones, we expect all of these categories to exhibit similar environmental

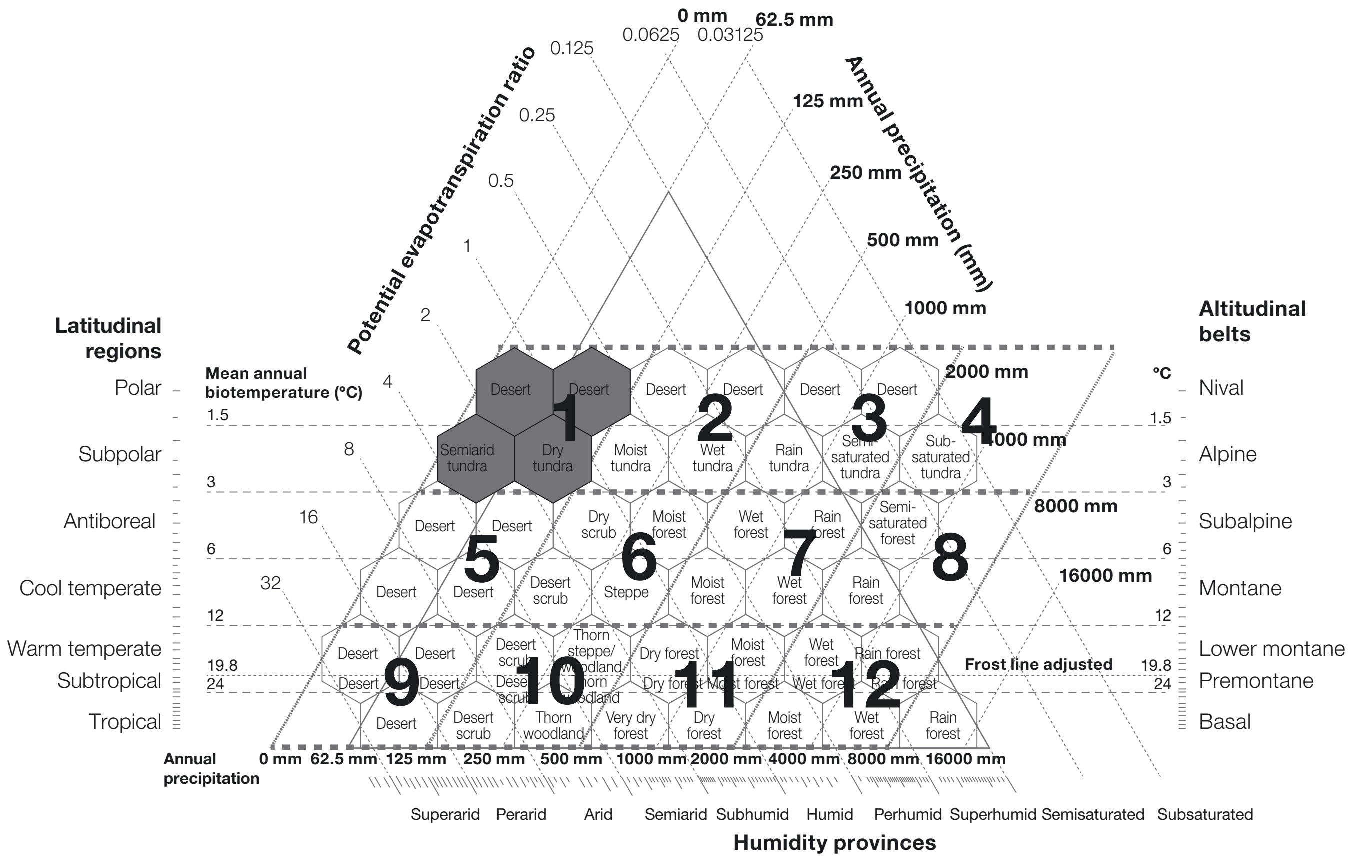

Fig. 2. Exemplification of reduced environmental resolution in the original Holdridge diagram (Holdridge 1947). In gray, the first group of life zones: the thicker dashed horizontal lines delimit broader ranges of biotemperature; thicker solid diagonal lines delimit wider ranges of precipitation

heterogeneity. By this procedure, the number of potential life zones was reduced to about a quarter of the original number.

2.4.4. LCD–GCD agreement and climatic and topographical heterogeneity

We analyzed the variations in the percent agreement across latitudinal regions to evaluate whether the agreement between LCD and GCD in the ecological land classification was affected by climatic differences. We also calculated an index of topographic complexity (H_t) for each latitudinal region, using the Shannon-Wiener diversity index (Shannon & Weaver 1963). For this, we classified a digital elevation model in 500 m intervals, and calculated 'pi' as the ratio between the land area contained in each altitudinal interval and the total area in the latitudinal region. We calculated the correlation between the percent agreement by latitudinal region and H_t using the Spearman correlation coefficient. We also calculated the correlation between the percent agreement and the total area in the latitudinal region to explore whether land conditions affecting the size of such regions influenced the percent agreement between LCD and GCD. Finally, we calculated the correlation between the percent agreement and a more explicit index of climatic variability given by the ratio between the number of life zones in the latitudinal region and the total area in the region (LZ/Area).

3. RESULTS

3.1. Uncertainty associated with local gridded data

The mean agreement between LCD and aLCD at the level of the whole country, through 1000 simulations, was about 75% and ranged slightly (between 62 and 82%) by latitudinal regions. However, there were important variations in the amplitude of the confidence intervals, with the largest amplitudes in the antiboreal (32–93%) and tropical regions (40–87%), and the smallest amplitude in the subtropical region (68–93%; Fig. 3).

3.2. Agreement between LCD and GCD compared with the uncertainty of the LCD

At the country level, the average agreement between ecological maps derived from LCD and GCD was 70%, but differed substantially across regions (40–83%). Yet, the percent agreement between LCD and GCD falls within the confidence interval of the LCD uncertainty, and this was true both at the level of the whole country as well as by latitudinal regions (see Fig. 3). At the same time, within the confidence intervals, the values of the LCD–GCD agreement tended to be lower than LCD–aLCD agreements. In the antiboreal and tropical regions, for example, the LCD–GCD agreement was near the lower confidence limit of the LCD–aLCD agreement (Fig. 3).

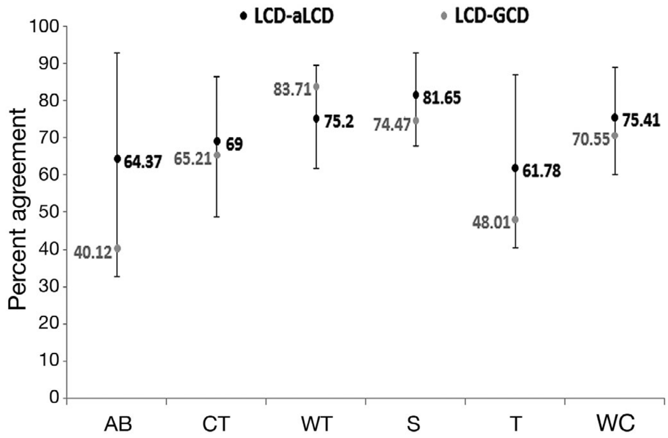

Fig. 3. Comparisons between local climate data (LCD) and global climate data (GCD) percent agreement (proportion of grid cells classified correctly), and LCD and altered LCD (aLCD) percent agreement and confidence intervals, for the whole country (WC) and for the latitudinal regions antiboreal (AB), cool temperate (CT), warm temperate (WT), subtropical (S), and tropical (T)

3.3. Spatial and environmental resolution of LCD–GCD agreement

Different measures of concordance between the maps of life zones of Argentina based on LCD and GCD showed that, at the level of the whole country, the agreements tended to remain constant for pixel sizes ranging between 1 and 50 km. However, at coarser resolution (50 to 1000 km pixels), grid cell agreement tended to decline, while percent agreement and chance agreement tended to increase (Fig. 4A). The same trend was found when reducing the thematic resolution (i.e. for the life zones map with fewer classes; Fig. 4B).

Similar patterns were observed for all latitudinal regions in decreasing grid cell agreement with decreasing spatial resolution above a 100 km pixel size, except the antiboreal region, for which the agreement decreased above 10 km pixel size.

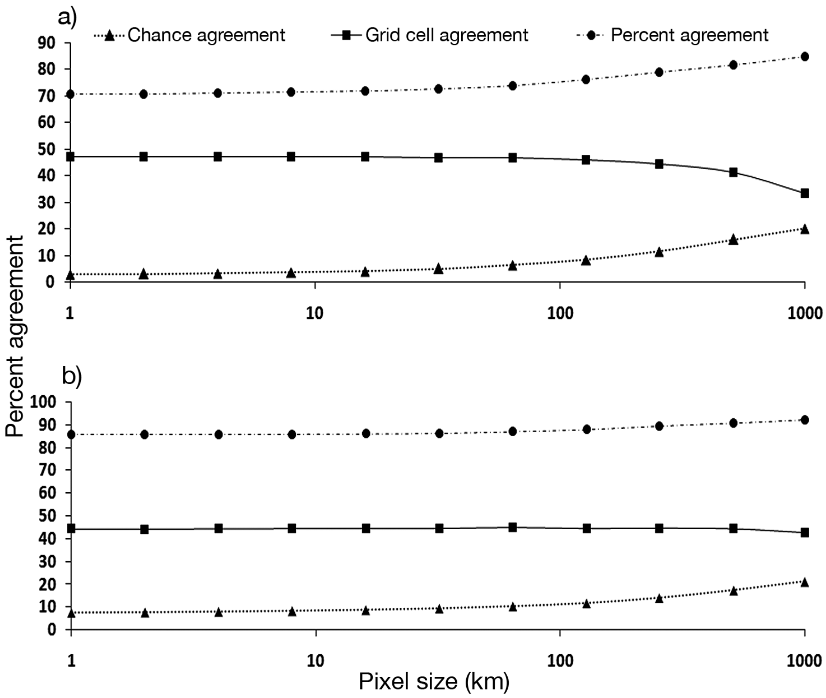

Fig. 4. Percent agreement (proportion of grid cells classified correctly), grid cell agreement (total proportion agreement without forced spatial agreement), and chance agreement (agreement that could be achieved with no information of location and no information of quantity) related to different pixel sizes for the whole country and related to (a) the original environmental resolution and (b) reduced environmental resolution

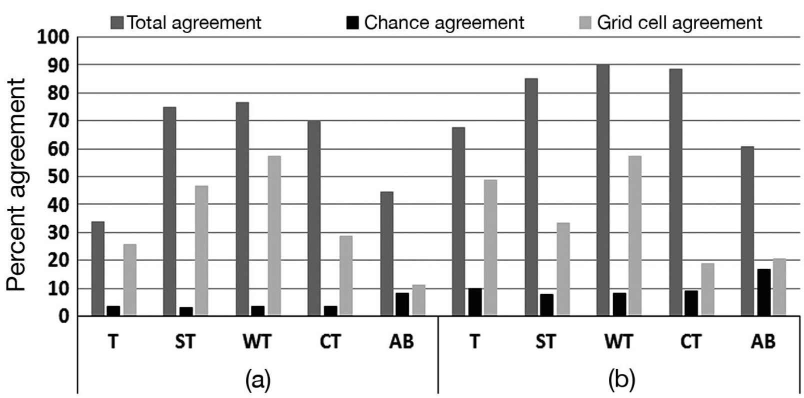

Fig. 5. Percent agreement, grid cell agreement, and chance agreement related to (a) the original environmental resolution and (b) reduced environmental resolution by latitudinal region (T: tropical; S: subtropical; WT: warm temperate; CT: cool temperate; AB: antiboreal)

When assessing the LCD–GCD agreement for the different latitudinal regions, we found that percent agreement and chance agreement increased when Holdridge life zones were combined (Fig. 5). However, the grid cell agreement showed a different trend, and only increased in the tropical and antiboreal regions (Fig. 5).

3.4. LCD–GCD agreement and climatic and topographical heterogeneity

We found that the percent agreement between LCD and GCD increased with the area (km^2) of the latitudinal regions ($r = 0.9$, $p < 0.05$; Fig. 6A), and decreased with increasing LZ/Area ratio (i.e. our measure of climatic variability; $r = -0.9$, $p < 0.05$, Fig. 6C). However, there was no relationship between LCD–GCD agreement and topographic complexity ($r = 0.1$, $p > 0.9$). For example, the 2 regions with lower LCD–GCD agreement exhibited the lowest (antiboreal) and highest (tropical) topographical complexity (Fig. 6B).

4. DISCUSSION

We found that the uncertainty of LCD can have important effects on the ecological land classification, although this effect strongly depended on environmental and climatic heterogeneity. At the level of the whole country, the average agreement between LCD and aLCD was around 75%, but in some regions the effect of uncertainty on the classification agreement was greater, such as in the tropical and antiboreal regions, where almost 40% of the land could be classified uncertainly using LCD. Although in our study area, the mean annual temperature and precipitation from LCD correlates well with meteorological stations (precipitation $r = 0.9898$, $p < 0.0001$ and temperature $r = 0.9458$, $p < 0.0001$; Derguy et al. in press), the differences between them might be large enough to cause an appreciable effect on the percent agreement.

In contrast, the differences in the ecological land classification based on LCD and GCD were similar to the differences associated with the uncertainty of the local data. Such differences varied appreciably among latitudinal regions. At the level of the whole country, the agreement between LCD and GCD was similar to the average percent agreement observed

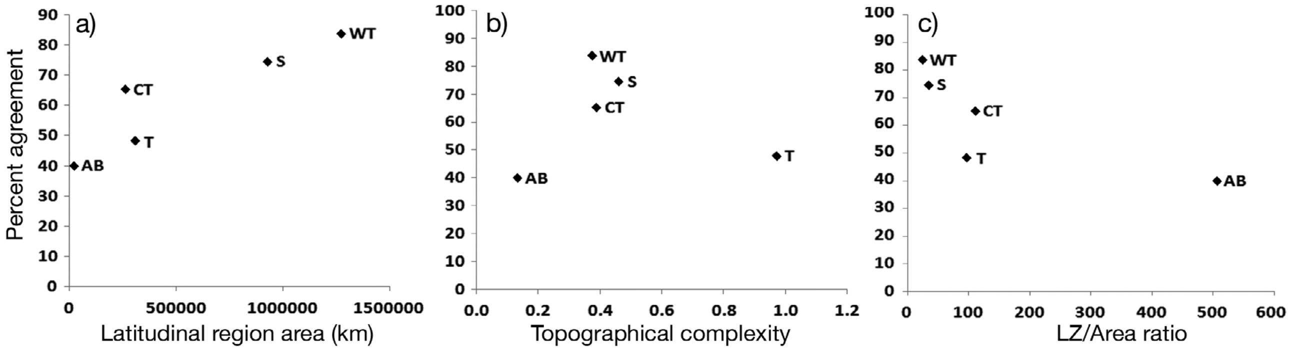

Fig. 6. Percent agreement as a function of (a) latitudinal region area (km^2), (b) topographic complexity, and (c) life zones (LZ)/latitudinal region area ratio for the different latitudinal regions (T: tropical; S: subtropical; WT: warm temperate; CT: cool temperate; AB: antiboreal)

in the comparison between LCD and aLCD. Moreover, the percent agreement of LCD–GCD per latitudinal region was also similar to LCD–aLCD percent agreement, suggesting that specific features at latitudinal region level similarly affected both comparisons. However, the percent agreement of LCD–GCD was very close to the lower confidence limit of the LCD–aLCD comparisons in the antiboreal and tropical regions. Therefore, local features leading to higher uncertainty in such regions affected GCD stronger than LCD.

Interestingly, the spatial resolution of LCD and GCD (1 km) seems to be too detailed, taking into account that in Argentina, the ratio between the number of meteorological stations and the land area (about 3 000 000 km^2) is far smaller than 1 station per square kilometer. The spatial resolution can strongly affect the comparisons of categorical maps (Chen et al. 2004, Lechner & Rhodes 2016) because the agreement means that the same category was assigned to the same pixels in both maps. The requirement of exact spatial coincidence does not take into account that equal labeled pixels could occur within a small spatial distance (Power et al. 2001, Pontius & Suedmeyer 2004). Thus, if neighboring pixels are aggregated by assigning the prevailing category to the new, greater pixel, the spatial noise decreases and agreement tends to increase. However, in spatially complex landscapes, high spatial resolution can increase the accuracy of land use classification based on satellite images (Chen et al. 2004). In our study, increasing the pixel size did not improve the agreement between LCD and GCD, which highlights that the spatial models underlying those gridded data are similar at high spatial resolution.

Thematic resolution is also a relevant feature affecting map comparisons (Lechner & Rhodes 2016) and landscape analysis. The agreement between categorical maps decreases if different categories are assigned to pixels that are environmentally similar (Power et al. 2001, Pontius & Suedmeyer 2004). Thus, the agreement between maps can increase by changing the thematic resolution (i.e. combining similar categories), as was found by Buyantuyev & Wu (2007) in landscape pattern analysis. In contrast, Salk et al. (2018) explicitly recommend not combining categories because this procedure increases the agreement by chance. In our study, we combined life zones to define environmental units based on broader ranges of biotemperature and precipitation. The percent agreement between LCD and GCD improved by reducing the environmental resolution at a higher rate than an increase in agreement by chance, especially in the latitudinal regions with low agreement. Thus, our study suggests that reducing the environmental resolution may be useful in some situations.

However, no clear trend in the association between the percent agreement per region and the topographic heterogeneity was found. A negative association between those variables was expected because the topographic heterogeneity affects the accuracy of the estimation processes of spatial models (Yao et al. 2013). The LCD–GCD agreement clearly tended to increase with the area of the latitudinal regions, because in the large, flat expanses, the estimates were similar for both climate data sources. This result suggests that in small but topographically complex regions, the percent agreement between LCD and GCD is low. This pattern seems to have been better accounted for by the ratio between the number of life zones and the area of each latitudinal region than the Shannon diversity index, which was used to assess the topographical heterogeneity. The number of life zones relates to the range of variation in bioclimatic conditions, so that a high range of variation, a small area, or the combination of both factors results in a high ratio, and represents an environmental variation at a small spatial scale. Thus, our study shows that high bioclimatic diversity in small areas constitutes a complex situation that promotes low agreement between maps, and such low agreement was improved by reducing the environmental resolution rather than the spatial resolution. The search for an appropriate thematic (environmental) resolution seems relevant when applying climate models.

Gridded climate data are a vital component of many ecological studies assessing current and future environmental conditions. Our study highlights the need to quantify the uncertainties in gridded climate data, especially in highly heterogeneous areas, and provides ways to quantify and deal with those uncertainties. Failing to understand the uncertainties in gridded climate data might lead to misleading resulting ecological assessments and forecasts.

Acknowledgements. This research was partially supported by the following institutions of the Argentina Republic: Consejo Nacional de Investigaciones Científicas y Técnicas (CONICET), Universidad Nacional de Avellaneda (UNDAV), and Laboratorio de Investigación de Sistemas Ecológicos y Ambientales (LISEA)-Universidad Nacional de La Plata. We thank G. Yañez, F. Nemiña, and M. Perez Flores for technical assistance and members of the laboratory (LISEA). Finally, we thank the subject editor and three anonymous reviewers for their valuable comments, which greatly improved our paper.

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Editorial responsibility: Tim Sparks, Poznan, Poland

Submitted: January 7, 2019; Accepted: August 09, 2019
Proofs received from author(s): October 08, 2019