**Material and methods**

Study area

Were selected thirty plots from National Forest Inventory of Spain (IFN) along tha Iberian Peninsula in function of aridity gradient (Villar et Sibecol, 2019), which were located in seven spanish regions with Mediterranean climate (mild rainy winters and hot and dry summers) (Cádiz, Córdoba, Sevilla, Toledo, Zamora, Lugo and Ourense). The annual temperature average oscillates between 17.3ºC (Cordoba) to 10.9ºC (Zamora) (World Climate, 2020) and the precipitation accumulated oscillates since annual 1582 mm (Lugo) until 321 mm (Toledo). In these places can find annual evapotranspiration accumulated with values since 1334 mm (Cordoba) until 978 mm (Lugo), data that create a large aridity gradient (precipitation/evapotranspiration) with high values like 1.61 (Lugo) until low values like 0.2751 (Toledo), more details about the selected places with different aridity gradient can be showed in Villar et al Sibecol (2019).

*Quercus ilex spp ballota* is forest specie adapted to Mediterranean climate conditions

The soil conditions are

The *P. pallida* dryland forests studied are located between 4º5′ – 6º22′ S and 79º00′ – 81º7′ W in the Piura Province (North-Western Peru, South America; Fig. 1). The geology is characterized by the presence of eolian and alluvial deposition and the topography is characterized by a semi-desertic plain (Bravo et al. 2003). The soil texture comprises more than 98% sand, except near the mountain foothills, where silt and clay reach 20% and 10%, respectively. The altitude varies between 15 and 232 m a.s.l. Even though this zone is located in a tropical area, the Humboldt Current flowing close to the Pacific coast of Peru reduces the annual precipitation and temperature. The climate is characterized by hot summers and mild, dry winters, with an annual average temperature between 23.4 and 24.8 ºC (Hijmans et al. 2005). Annual precipitation averages between 48 (73 m a.s.l.) and 354 mm (232 m a.s.l.) and occurs in summer (January to March), resulting in a long winter drought of 8-9 months (from April to December) (Bravo et al. 2003). The variation in altitude, temperature, and precipitation indicates the presence of a climatic gradient related to the altitude, which increases from the coast to the foothills (Fig. 1 and Table 1), while the proximity to the Pacific Ocean also provides a gradient of evapotranspiration, which decreases as one moves further inland. The climatic variability in this area is highly affected by the ENSO, which creates a dry phase of 5-10 years (with the climatic conditions described before) and a wet phase of 1-2 years (with an increase in air temperature of 1-2 °C and an increase in annual precipitation of up to 2000 mm) (Erdmann et al. 2008). These extreme precipitation events are major drivers of alluvial depositions and, alongside wind dispersal, control the soil surface nutrient composition in the North-Peruvian coastal areas (Wells 1990; Li et al. 2008). Soil and leaf samples were taken in summer 2014, during the dry phase of the ENSO cycle. During this phase, highly stable climatic conditions are found and the monthly temperature variability fits a sine wave with a phase length of one year (Rollenbeck et al. 2015). The last significant ENSO event prior to the sampling date occurred in 1998.

*Sampling design and data collection*

The sampling process was carried out in summer 2014 during one month period. Seven *P. pallida* populations were selected to cover the variation in soil properties and nutrient concentrations, as well as in altitude, temperature, and precipitation along a climatic gradient (Table 1; Fig. 1). This study is part of large experimental project, and the variability between sites in terms of plant functional traits have been address before (Salazar et al. 2018b; Salazar Zarzosa et al. 2019). Therefore, we expected a similar pattern in the soil and leaf nutrients. Since one of them (Ñapique) presented high site variability related to its proximity to a lake, this location was considered as two different populations (Ñapique Wet and Ñapique Dry, the former being closer to the lake). Therefore, we considered a total of eight populations. Thus, the populations ordered according to mean annual precipitation were Piura (PI), Rinconada (RI), Quebrada Soledad (QS), Ñapique dry (ND), Ñapique wet (NW), Locuto (LO), Ignacio Tavara (IT), Rio Seco (RS). The population proximity to bodies of water (rivers) were also recorded. However, the river flow was relatively low (50-100 m3 s-1) and it is mainly use for agriculture and human consumption. These locations represent most of the North-Peruvian dryland forests, where the plant cover is mainly dominated by *P. pallida* trees. To cover the spatial and microclimatic variability within each site, three plots (of ca. 1 ha each) per population were established. The average distance between plots was 1265 m, to avoid pseudo-replication. Within each plot, a random sampling inventory was developed and five adult trees of *P. pallida*, with a basal stem diameter exceeding 10 cm at breast height, were selected, giving a total of 120 trees (experimental units) across all populations, with a 20 m average distance between them. Individual tree locations were recorded with a real-time differential global positioning system (GPSMAP 76CSx - Garmin USA International, Inc; estimated position error <1 m).

In each tree, a fully-expanded, sun-exposed branch was selected and mature leaves with no signs of damage were collected and transported to the laboratory in hermetic bags, to measure leaf nutrient concentrations. Two meters from each tree, soil samples (8 cm in diameter) were collected using a steel core sampler, at a depth of 0-25 cm from the topsoil surface, and stored in hermetic bags until they were processed in the laboratory. All soil samples were air-dried, and coarse soil particles were removed with a stainless steel sieve (mesh size 2 mm) before elemental analysis.

*Soil and leaf analysis*

We measured the concentrations of macronutrients (N, P, K, Ca, and Mg) and micronutrients (Fe, Mn, Cu, and Zn) in the soil and leaves. The total N in the soil samples was determined by dry combustion, after grinding, using an elemental analyzer (Eurovector EA3000; EuroVector SpA, Milan, Italy) (Wang and Anderson 1998). Available P (Olsen et al. 1982) was determined according to the molybdate blue method (Murphy and Riley 1962). The K, Ca, and Mg were determined by atomic absorption spectrophotometry, after extraction with 1 M NH4OAc at pH 7. The Fe, Mn, Cu, and Zn were determined by atomic absorption spectrophotometry after extraction with a solution containing 0.1 M triethanolamine (TEA), 0.005 M diethylenetriaminepentaacetic acid (DTPA), and 0.01 M CaCl2 (Norvell and Lindsay 1972). Soil texture was measured in 50 g of soil using the Bouyoucos hydrometer method (Bouyoucos 1962). Soil pH was determined in a 1:2 (w/v) soil/water extract, using a pH meter (Crison GLP 21, Hach Lange, Spain), and EC in a 1:5 extract, using an electrical conductivity meter (Crison model basic 30, Hach Lange, Spain). The soil Na in the latter extract was determined by atomic absorption spectrophotometry, and it was used to obtain the soil sodium adsorption ratio (SAR) according to:

Leaves were dried at 70 °C for 24 h before grinding with a stainless steel grinder. Then, the leaf N concentrations were measured using an elemental analyzer (Eurovector EA3000), and the other elements were determined after digestion with a nitric-perchloric acid mixture (Zasoski and Burau 1977), using the same methods described for the soils.

*Statistical analysis*

First, we used leaf stoichiometry (the ratio between nutrients and C concentration) instead of leaf nutrient concentration to study the elemental composition (Urbina et al. 2015). However, leaf stoichiometry and leaf nutrient concentration showed nearly the same results, so we used the latter for the sake of simplicity. We examined the fit of all variables to the assumptions of normality and homogeneity of variance, using the Shapiro-Wilk and Levene test, respectively. All variables were normalized by log10 transformations. To know the importance of the three sources of variability (tree, plot, and population level) in the soil and leaf nutrient concentrations, we used the restricted maximum likelihood (REML) method in the lme function of the "nlme" package of R. We fitted a general linear model to the variance across the three scales, nesting one into another in this increasing order: tree, plot, population. The amount of variance explained at each level and the coefficient of variation (CV) of each nutrient determine the nutrient variability in the leaf. CV was calculated as the standard deviation divided by the mean (× 100).

To know the relationships among soil nutrients we used a Principal Component Analysis (PCA) for all the soil nutrients. An ANOVA and a Tukey HSD post-hoc analysis were performed using the individual scores of the two main axes of the PCA, to determine the significant differences between populations. A similar approach was taken for the leaf nutrient concentrations, and nutrient score values from each PCA axes was recorded (Online Resource 1). We explored the relationships between the soil chemical attributes, and the soil and leaf nutrient concentrations, as well as between the main soil and leaf axes of the PCAs, using Pearson's correlations. Due to the high amount of variability in these variables, we chose not to apply a Bonferroni correction in the p-values, to avoid the deletion of correlations with biological causes but a low correlation coefficient. Finally, to explain the causal relationship of soil chemical attributes and soil and leaf nutrients, we built a structural equation model (SEM) with the “lavaan” package, using untransformed data. The structure of the hypothesized causal relationships between selected variables was set based in our hypotheses and the Pearson correlation results and later slightly modified as a function of the highest statistical support according to the significance of chi-squared (*P* > 0.05), indicating that the covariance pattern predicted by the model is indistinguishable from the observed (Alameda et al. 2012). In the SEM, we used the PCA axes to reduce the amount of variables to a linear combination of smaller components instead of creating composite variables. The “lavaan” package have compiling issues to create composite variables (especially if there is more than one) and some authors (Grace and Bollen 2008) have suggested to calculate the estimates manually. To avoid this (and make a reproducible work) we decided to use the PCA axes instead. A prior model based on the expected effect of soil fertility on leaf nutrients is included in the Online Resource 2. All statistical analyses were carried out using R software (R Core Team 2017), using all the trees and soil samples (n = 120).