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Spatial analysis and risk mapping of *Fasciola hepatica* infection in dairy cattle at the Peruvian central highlands

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A R T I C L E I N F O

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A B S T R A C T

This study aimed to develop maps for *Fasciola hepatica* infection occurrence in dairy cattle in the districts of Matahuasi and Baños in the Peruvian central highlands. For this, a model based on the correlation between environmental variables and the prevalence of infection was constructed. Flukefinder® coprological test were performed in samples from dairy cattle from 8 herds, during both the rainy and wet season. Grazing plots were geo-referenced to obtain information on environmental variables. Monthly temperature, monthly rainfall, elevation, slope, normalized difference vegetation index (NDVI), enhanced vegetation index (EVI), normalized difference water index (NDWI), distance to rivers, urban areas and roads were obtained by using remote sensor images and ArcGIS®. Multilayer perceptron Artificial Neural Networks modeling were applied to construct a predictive model for the occurrence of fasciolosis, based on the relationship between environmental variables and level of infection. Kappa coefficient ($k > 0.6$) was used to evaluate concordance between observed and forecasted risk by the model. Coprological results demonstrated an average prevalence from 20% to 100%, in Matahuasi, and between 0 and 87.5%, in Baños. A model with a high level of concordance between predicted and observed infection risk ($k = 0.77$) was obtained, having as major predicting variables: slope, NDWI, NDVI and EVI. Fasciolosis risk was categorized as low ($p < 20\%$), medium ($20\% < p < 50\%$) and high ($p \geq 50\%$) level. Using ArcGIS 10.4.1, risk maps were developed for each risk level of fasciolosis. Maps of fasciolosis occurrence showed that 87.2% of Matahuasi area presented a high risk for bovine fasciolosis during the dry season, and 76.6% in the wet season. In contrast, 21.9% of Baños area had a high risk of infection during the dry season and 12.1% during the wet season. In conclusion, our model showed areas with high risk for fasciolosis occurrence in both districts during both dry and rainy periods. Slope, NDWI, NDVI and EVI were the major predictors for fasciolosis occurrence.

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1. Introduction

The parasitic trematode *Fasciola hepatica* infects ruminants and other domestic animals and forms a major parasitosis in livestock around the world. Additionally, this parasite is an important zoonosis in the Andean region (Mas-Coma et al., 2008). The parasite's life cycle involves a definitive host (mammals) and an intermediate host, a lymnaeid snail (Giraldo and Álvarez, 2013). *Galba truncatula* and *Lymnaea* spp. are the most common lymnaeid hosts for *F. hepatica* in the Andean countries (Bargues et al., 2011). These gastropods live in freshwater aquatic environments and have shown great adaptability to different geographical areas (Fuentes et al., 2001). Their ample distribution and its high-biotic potential under favorable conditions favor the presence of *F. hepatica* in almost all continents (Carrada, 2007).

Fasciolosis causes important productive and economic losses in livestock (Charlier et al., 2014). The negative impact of this parasitosis is the result of an increase in mortality and the costs associated with frequent treatments, condemnation of infected livers, reproductive failures and reduction in milk and meat production (Schweizer et al., 2005). South American.

countries such as Brazil, Colombia and Bolivia have endemic and/or hyper-endemic areas for.

bovine fasciolosis (Pinilla et al., 2020; Molento et al., 2020; Mas-Coma et al., 2020). Peru also presents high rates of infection in cattle, especially in the highlands (Arias-Pacheco et al., 2020). The Mantaro Valley showed hyper-endemic areas, such as the District of Matahuasi, with rates of infection over 90% (Briones-Montero et al., 2020). Fasciolosis is a major zoonosis in the Peruvian highlands' rural communities with children as the most affected population (Espinoza et al., 2010).

The characterization of *F. hepatica* epidemiology is vital to assess the factors involved in the occurrence of fasciolosis. Climatic and environmental factors (atmospheric temperature, rainfall, soil, humidity, vegetation, etc.) can account for 70 to 76% of parasitosis variation in determined areas (McCann et al., 2010). These variables are crucial for the viability and development of the parasite and its snail host since both quickly respond to variations in environmental conditions. Any effect on their survival and development rate could produce a rise in the risk for transmission (Howell et al., 2015; Sangwan et al., 2016).

Geographic information systems (GIS) and remote sensing have been used in animal health research to perform studies on spatial

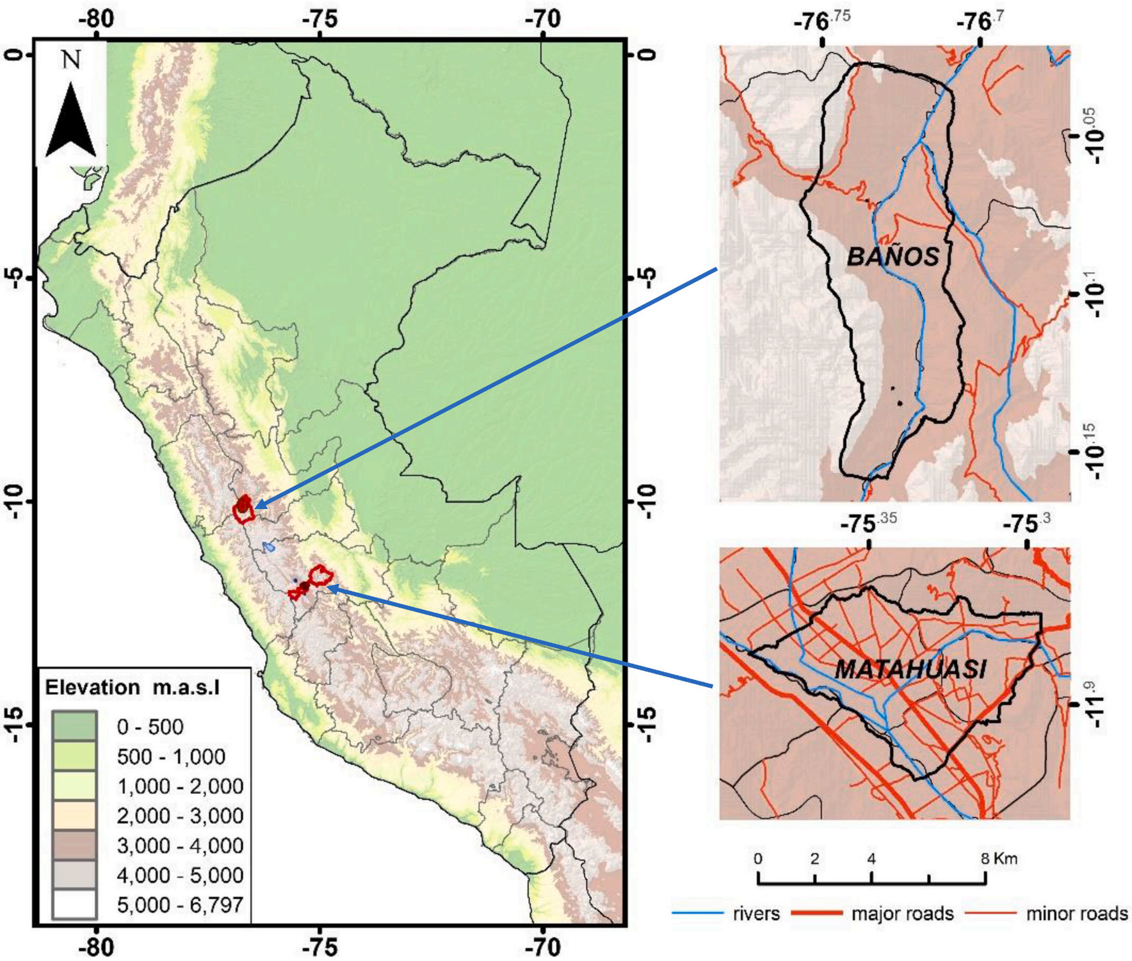

Fig. 1. Location of the districts of Baños and Matahuasi in Peru.

epidemiology, create maps for disease prevalence and forecast models for infection risk (Carpenter, 2011; Villa-Mancera and Reynoso-Palomar, 2019a). These tools enable tracking of areas with a risk of bovine fasciolosis through the identification of environmental factors associated with cattle infection (Sun et al., 2020). This approach is a key component in supporting improved and sustainable programs for bovine fasciolosis. There are several examples of applying GIS and geospatial tools to identify zones with high risk of fasciolosis in different countries. For example, Ducheyne et al. (2015) elaborated *F. hepatica* risk maps in five European countries by using GIS to rank climatic and environmental variables as risk factors through decision tree algorithms. Similarly, in Ireland, risk maps for fasciolosis were made by relating prevalence of infection to several environmental predictors, such as temperature, rainfall and vegetation by using the random forest methodology as a tool for infection risk modeling (Lucena et al., 2018).

These types of epidemiological studies are not limited to Europe, for instance, in China, environmental factors with higher association with *F. hepatica* development were identified through spatial instruments and based on this analysis, risk maps were developed (Qin et al., 2016). Regarding reports from South America, in the regions of Espirito Santo in Brazil, a theoretical algorithm, based on data previously published, was used to perform risk analysis for fasciolosis (Vilhena Freire Martins et al., 2012). Freitas et al. (2014) developed a forecasting risk model for *F. hepatica* infection in the same Brazilian region using linear regressions and ranked different variables according to a decision matrix created by an Analytical Hierarchy Process (AHP). A much more elaborated approach was performed in Colombia, where a climate-based risk model for bovine fasciolosis at a country level was constructed using prevalence data and a mathematical model of maximum entropy (MaxEnt), originally developed for modeling of ecological niches (Valencia-López et al., 2012). The Artificial Neural Networking (ANN) constitute a modeling approach based on machine learning. This strategy can yield optimal models that reflect the structure of complex and hidden interrelationships among variables (Pitarque et al., 1998). These characteristics allow the organization of large data sets when complex information, with an unknown distribution, is provided. This approach has been used for epidemiological studies related to the occurrence of diseases (Aiken et al., 2021; Fritz et al., 2022). Moreover, published antecedents support the application of ANN for forecasting fasciolosis infection in dairy cattle. (González-Díaz et al., 2010; Sánchez-Moret, 2016).

Only a few studies on the use of GIS to monitor fasciolosis in Peruvian territory have been reported. One study created an epidemiological model for zoonotic fasciolosis in Peru and other South American countries, based on climatic and vegetation indices, obtained from satellite images, to forecast *F. hepatica* infection (Fuentes et al., 2005). However, this model was purely theoretical and based on mathematical modeling, with no field data collected on infection levels. A more recent study used GIS to assess the geospatial association between livestock fasciolosis and risk for human infection in an endemic area of the Peruvian highlands (Tanabe et al., 2022). Considering the ample geographical and climatic variability of the Peruvian highlands, it is recommendable to perform these types of studies in specific zones to develop maps for the occurrence of fasciolosis in limited areas. The main goal of this study was to develop maps for the occurrence of fasciolosis in dairy cattle in two districts of the Peruvian central highlands by collecting field data, applying GIS and through an Artificial Neural Networks model (ANN).

2. Material and methods

2.1. Study area

This research was carried out in the districts of Baños, Lauricocha, Huanuco Region and Matahuasi, Concepción, Junín Region (Fig. 1). According to the ecological life zones classification, both districts are located in the tropical montane wet forest and tropical lower montane dry forest ecosystems, respectively (Castro et al., 2021). The study area in Baños had a surface of 54.67 km^2, whereas in Matahuasi covered 35.14 km^2. Both districts have moderate and cold weather, having two marked periods: wet season (between November and May) and dry season (between June and August). The land use in both districts is for agriculture and livestock activities. Both districts are important milk producing areas, with dairy cattle raising as one of the major economic activities. Cattle are fed grass in cultivated pastures, scattered around the districts, and normally located kilometers away from the stables so that the herds must move great distances every day. Grazing plots are concentrated in common areas shared by most of the farms in specific zones in each

Table 1
Number of individual fecal samples collected from dairy cattle (N) during the study and the overall percentage of *Fasciola hepatica* infection ± 95% Confidence interval (95% CI) in the districts of Matahuasi and Baños.

SEASON	MATAHUASI			BAÑOS		
	Month, year	N	Percentage of infection (%) ± 95% CI	Month, year	N	Percentage of infection (%) ± 95% CI
Wet	February 2016	50	60.00 ± 13.6	February 2016	57	43.86 ± 12.9
Dry	July 2016	51	80.39 ± 10.9	July 2016	55	65.45 ± 12.6
Wet	December 2016	53	75.47 ± 11.6	November 2016	56	53.57 ± 13.1
Wet	February 2017	57	85.96 ± 9.0	March 2017	58	48.28 ± 12.9
Dry	June 2017	56	76.79 ± 11.1	August 2017	54	37.04 ± 12.9
	TOTAL	267		TOTAL	280	

district. Bovine fasciolosis is a major parasitosis in both districts, compromising public health as well. Districts were also selected based on their topography differences, despite their similar altitude and climate. Baños has steeper slopes and more accidental rangelands than Matahuasi, which is located in the middle of a wider valley.

2.2. *Fasciola hepatica infection*

According to the National census of 2012, the district of Matahuasi had 637 dairy herds, of which 80% (500) consisted of <10 animals; 531 farms were registered in Baños, of which 50% (244) had <10 animals (Instituto Nacional de Estadística e Informática INEI, 2012). Eight dairy herds were selected based on their number of animals: between 15 and 20 animals; and the geographic location of their grazing plots: covering different altitudinal zones and at different distances to rivers and roads. Limitations on the accessibility to grazing plots also influenced the number and criteria for selection of herds. To assess the level of infection in each herd, 20 % of the adult cattle population in each herd was sampled (Thrusfield, 2007). These sampled animals were used as sentinel individuals and evaluated during each season of the year (wet and dry) to obtain a reference on the infection level in each herd and area evaluated. Animals had not been dewormed at least two months before a sample collection. Due to culling and replacement of some milking cows in the herds, there were variations in the sample size during the study. Fecal samples from adult grass-fed dairy cows (between 2 and 4 years) were obtained directly from the rectum in wet and dry periods during 2016 and 2017 (Table 1). Feces were taken to the Laboratory of Parasitology of the Animal Science College at the Universidad Nacional Agraria La Molina (UNALM), in isothermal cool boxes with gel packs. Mineral oil and disposable obstetrical gloves were always used to ensure the animal welfare during the sampling. The Flukefinder® (Flukefinder, USA) test was used, according to the manufacturer's instructions, to detect *F. hepatica* eggs. This test has shown to have a sensitivity of around 80% and a specificity above 90% compared to sedimentation techniques (Kurnianto et al., 2022) and up to 100% sensitivity when tested in artificially spiked stool samples (Zárate-Rendón et al., 2019). The level of infection was expressed in percentage of positive animals and 95% confidence intervals were obtained using Microsoft Excel v. 16.0 (MSO, Versión 1804), applying the Analysis ToolPak and the Solver Add-in packages. Due to the characteristics of the ANN modeling approach applied, which works better using categorical response variables, the percentage of infection in each dairy herd was categorized arbitrarily into three categories: low ($p \leq 20\%$), medium $21\% \leq p \leq 50\%$) and high ($p \geq 51\%$) and this approach was used to infer the risk of infection.

2.3. *Digitization and Geo-referencing of study areas*

Areas were digitized through Aeronautical Reconnaissance Coverage Geographic Information System (ArcGIS®) v. 10.4.1 software (Esri Inc., USA) in vectorial format polygon type. Such areas were classified in agricultural and/or grazing plots, urban areas, roads, forest areas, mountains and rivers. Each grazing plot used by a herd was geo-referenced (x and y coordinates) using the Global Positioning System (GPS) (GPS, Garmin®). The location of grazing plots used by the sampled herds changed during the study so that data were updated for the analysis.

2.4. *Environmental and climatic variables*

For developing of maps of occurrence and risk for fasciolosis, certain environmental variables were selected as potential variables associated to infection. Selection was based on recently published studies and the following variables were chosen: monthly atmospheric temperature (°C), monthly rainfall (mm) (Lucena et al., 2018), elevation (masl) (Kuerpick et al., 2013; Pinilla et al., 2020), slope (°) (Vilhena Freire Martins et al., 2012), distance to rivers (m), distance to urban areas (m), distance to roads (m) (Tum et al., 2004), normalized difference vegetation index (NDVI), which is related to the reflectance of the near infrared and thus related to the photosynthetic activity and vegetation health; enhanced vegetation index (EVI), which constitute a better option to the NDVI when there is too much reflectance in the near infrared; and normalized difference water index (NDWI), which is related to the humidity content in vegetation and soil (Lucena et al., 2018; Sun et al., 2020) . Variable information was obtained from geo-referenced grazing plots for each herd, during wet and dry season months in 2016 and 2017. All the information from the same variables obtained for the total digitized area in Matahuasi and Baños districts was also obtained. For the case of each grazing plot, values were calculated to the centroid of the polygon.

2.4.1. *Temperature and rainfall*

Information regarding monthly temperatures was obtained through satellite images of 50 km resolution acquired from NASA GIOVANNI website (https://giovanni.gsfc.nasa.gov/giovanni/). Information on monthly rainfall was derived from data from the National Peruvian Service of Meteorology and hydrology (SENASA-PISCO) (http://ons.snirh.gob.pe/SOURCES/.Peru/.SENAMHI/.PISCO/.Precipitation/.Monthly/). The satellite images used had a spatial resolution of 5 km.

2.4.2. *Distance to rivers, roads and urban areas*

Distances to rivers, roads and urban areas, in meters, for each herd were obtained by using ArcGIS v. 10.4.1 (Esri Inc., USA) through the "Euclidean distance" spatial analysis tool to determine the distance to the centroid.

2.4.3. *Elevation and slope*

All the information regarding elevation in meters above the sea level (masl) as well as the slope in grades (°) were deduced by analyzing satellite images from ALOS PALSAR satellite acquired from Alaska Satellite Facility (https://vertex.daac.asf.alaska.edu/). The images had a spatial resolution of 12.5 m. Additionally, for the slopes, images were processed through ArcGIS® v. 10.4.1 using the tool for spatial analysis "slope".

2.4.4. Vegetation and water indices

Satellite images (spatial resolution of 10 m) from Sentinel 2 satellite were used to obtain NDVI, EVI and NDWI. These images were extracted from the USGS source (https://glovis.usgs.gov/app) and processed using ENVI® v. 5.3 (Exelis visual information solutions Inc., USA). The following formulas were applied to calculate NDVI, EVI y NDWI:

$$\mathrm{NDVI} = \frac{(\mathrm{NIR} - \mathrm{RED})}{(\mathrm{NIR} + \mathrm{RED})}$$

$$\mathrm{EVI} = \frac{2.5 \times (\mathrm{NIR} - \mathrm{RED})}{(\mathrm{NIR} + 6 \times \mathrm{RED}) - 7.5 \times \mathrm{BLUE} + 1}$$

$$\mathrm{NDWI} = \frac{(\mathrm{GREEN} - \mathrm{NIR})}{(\mathrm{GREEN} + \mathrm{NIR})}$$

where:

NIR: Band 8 near infrared (842 nm).
RED: Band 4 red (665 nm).
BLUE: Band 2 blue (490 nm).
GREEN: Band 3 green (560 nm).

2.5. Modeling

Statistical models were structured using multilayer perceptron Artificial Neural Networks models (ANN) in Statistical Package for the Social Sciences software (SPSS)Statistics® v. 22 program (IBM Corp., USA) considering climatic and environmental factors, acquired in each geo-referenced grazing plot for herd at each district, as independent variables and *F. hepatica* prevalence, categorized arbitrarily into high, medium and low risk, as explained before, as dependent variable. Elaborated models were evaluated according to the correct percentage forecasted at the training qualification and ANN testing, which indicate the similarity level between expected and obtained result by test repetition in different sub-samples of the total sample. Seventy per cent of the data was processed for model training and 30% for testing. The ANN training used a batch size of 1, with forward propagation, two hidden layers with sigmoid function and softmax output function, learning rate of 0.01, momentum of 0.9, error ratio of 0.001 and weight decay values of 10–4. Each model, according to their component independent variables, yielded a *F. hepatica* risk probability. Multilayer perceptron ANN was used as categorical predicting algorithm using the selected variables as predictors in the first step (Aiken et al., 2021; Fritz et al., 2022). Since the main goal of our study was to develop an overall ANN model for fasciolosis distribution and risk maps, in dairy cattle, based on this model under the environmental conditions of the Peruvian central highlands, considering the common raising conditions for herds in this region; a single model was developed. Kappa (k) symmetric test performed with SPSS Statistics® v. 22 (IBM Corp., USA) was applied to evaluate concordance between *F. hepatica* risk probability results from the models and those from the field observations. The model with a kappa coefficient higher than 0.6 was chosen since it was considered acceptable (Pinilla et al., 2020; Kurnianto et al., 2022).

2.6. Risk map construction

By using the selected model, spatial distribution maps for Matahuasi and Baños districts were created, for both dry and wet season, based on the relationship among environmental and climatic variables as well as *F. hepatica* prevalence obtained during the period 2016–2017. The maps were constructed using ArcGIS® v. 10.4.1 (Esri Inc., USA) software. Vectorial layer format conversion (for digitized areas) to a new pointed vectorial layer was made, and all the information from environmental and geographical variables obtained from the digitized grazing plots were introduced into the new pointed layer. Each point corresponded to a sampling point and they had X, Y geographical coordinates. After having all data in an Aeronautical Reconnaissance Coverage Map (ArcMap®) attribute table, this table was exported in a tabular format to SPSS Statistics® v. 22 software. Then, according to the accepted statistical risk model, predicted *F. hepatica* risk values for each point of digitized area were obtained. Using ArcGIS 10.4.1, the forecasted value saved file was opened, then, X, Y coordinates data was added; and, finally, vector format (polygons) risk maps, showing low, medium and high *F. hepatica* exposure risk for dairy cattle during dry and wet season were constructed.

3. Results

3.1. Fasciola hepatica infection

In the district of Matahuasi, general levels of infection in the total of sampled animals ranged from around 60% (February 2016) to

85.96% (February 2017). In Baños, these percentages varied from around 37.04% (August 2017) to 65.45% (July 2016). The distribution of levels of infection in each herd during the four sampling periods is shown in Fig. 2. In the Matahuasi district, the herd prevalence ranged from 20% to 100% (average of 76.21 ± 7.4%), whilst in Baños percentages varied from 0% to 87.5% (average of 46.54 ± 9.5%).

3.2. Climatic and environmental variables

Information on environmental temperature and rainfall obtained for each grazing plot in each herd during the study is shown in Fig. 3. A clear seasonality can be observed with differences in rainfall and temperature, especially in 2016.

Fig. 4 shows the distances from the grazing plots, for each dairy herd, to rivers, roads and urban areas during the study period. These vary over the year due to the need for suitable pastures, scattered all around the district and whose availability is limited. Over 70% and 80% of the grazing plots were at a distance longer than 100 m to the closest rivers, in Matahuasi and Baños, respectively. Regarding distances to main roads, in both districts, all the grazing plots were located >100-m distance to these. >55% of grazing plots in both districts were located at a distance >100 m to urban areas.

Information on the elevation (masl) and slope (°) acquired from each grazing plot used by herds in both districts are shown in Fig. 5. Pasturing areas in Matahuasi were located at a lower elevation than those in Baños (3319.r masl versus 3597 masl in average, respectively) and, moreover, Matahuasi pastures were less steep (2.8° vs. 11.2° average, respectively).

Values for NDVI and EVI (vegetation indices) and NDWI (water index) for each grazing plot can be observed in Fig. 6. In Matahuasi, NDVI values ranged from 0.14 to 0.83, whereas in Baños from 0.27 to 0.84. Regarding EVI values, they varied from 0.06 to 0.83 in Matahuasi, and from 0.14 to 0.88 in Baños. In the two districts, NDVI and EVI values were higher during the wet season. For NDWI, Matahuasi values varied between −0.72 and −0.26; whilst in Baños ranged from −0.72 to −0.37. Values, for both districts, did not show a seasonal pattern.

3.3. Predictive statistical model

The best predictive model developed through ANN obtained a training percentage of 89.4% and a test percentage of 85.7% (Table 2), which indicated that the risk of *F. hepatica* obtained through the observed prevalence and the risk of infection predicted by the model had a high degree of concordance. This was corroborated by the value of the Kappa coefficient obtained from the model (k = 0.78). Fig. 7 shows the environmental variables involved in the model and their normalized importance expressed as a percentage.

According to our model, slope degree (°) was the predictor variable with the biggest influence on the risk of infection, with an importance value of 100%. Apparently, the steeper the slope degree, the lower the infection risk of fasciolosis. The vegetation and water indices (NDVI, EVI and NDWI) were of considerable importance in our model, showing percentages >86%. The model constructed showed a positive relationship between NDWI and the risk of infection. For the vegetation indices the relationship was unclear although it showed a trend to be inverse. The distance to rivers was also considered an important variable in this model (83.8%). The distances to urban areas had moderate importance (63.7%) in contrast to the distance to roads (7.9%). Likewise, elevation had minimal importance (16.3%) in the model. According to the developed model, both precipitation and ambient temperature were less important in explaining the risk of fasciolosis compared with other variables.

3.4. Maps for occurrence of F. hepatica infection

The spatial distribution of bovine fasciolosis, categorized in low, medium and high risk, during the dry and wet seasons in Baños and Matahuasi is shown in Fig. 8 and Fig. 9. Our results suggest that 87.2% areas of Matahuasi presented a high risk of bovine fasciolosis during the dry season, and 76.6% during the rainy season. Similarly, the areas identified as moderate risk were 8.1% in dry

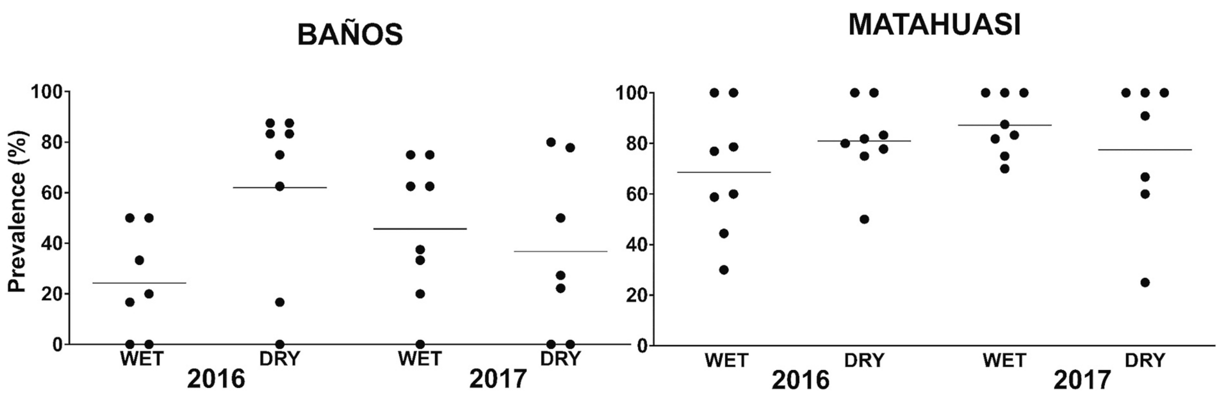

Fig. 2. Percentage of *Fasciola hepatica* infection in dairy cattle at herd level ($n = 8$) during the wet and dry seasons of 2016–2017 in the districts of Matahuasi and Baños. Each dot represents a herd sampled and lines represent arithmetic average.

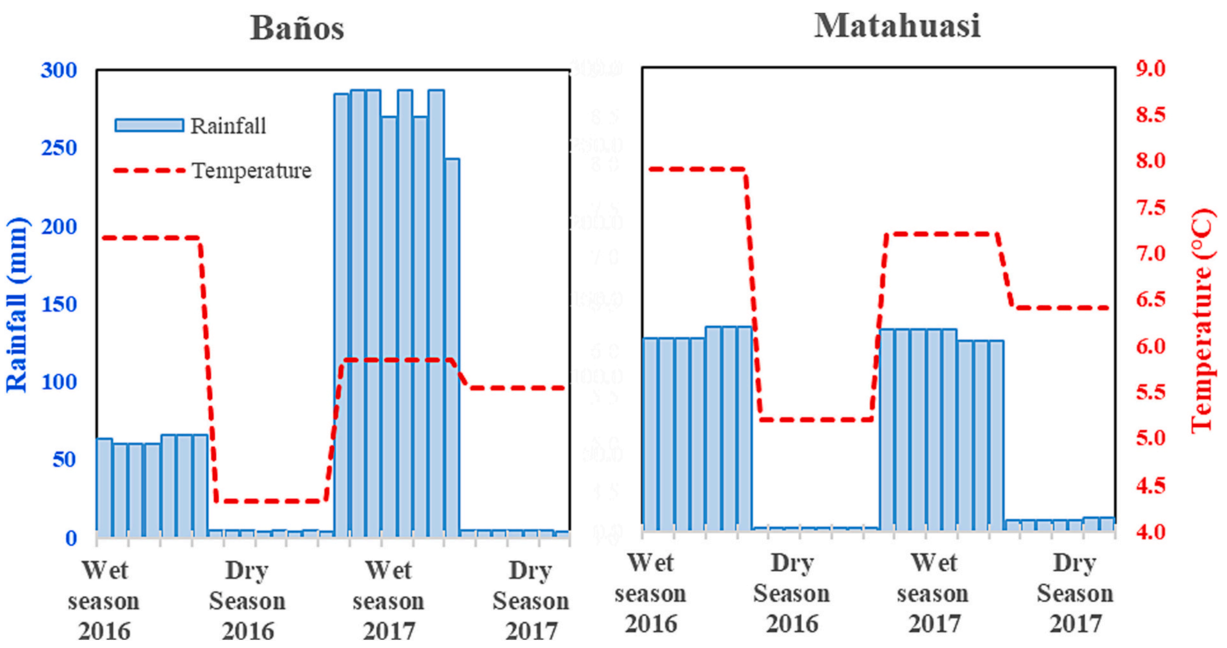

Fig. 3. Rainfall (mm) and mean temperature (°C) from the geo-referenced grazing plots at the districts of Matahuasi and Baños during wet and rainy season (2016–2017).

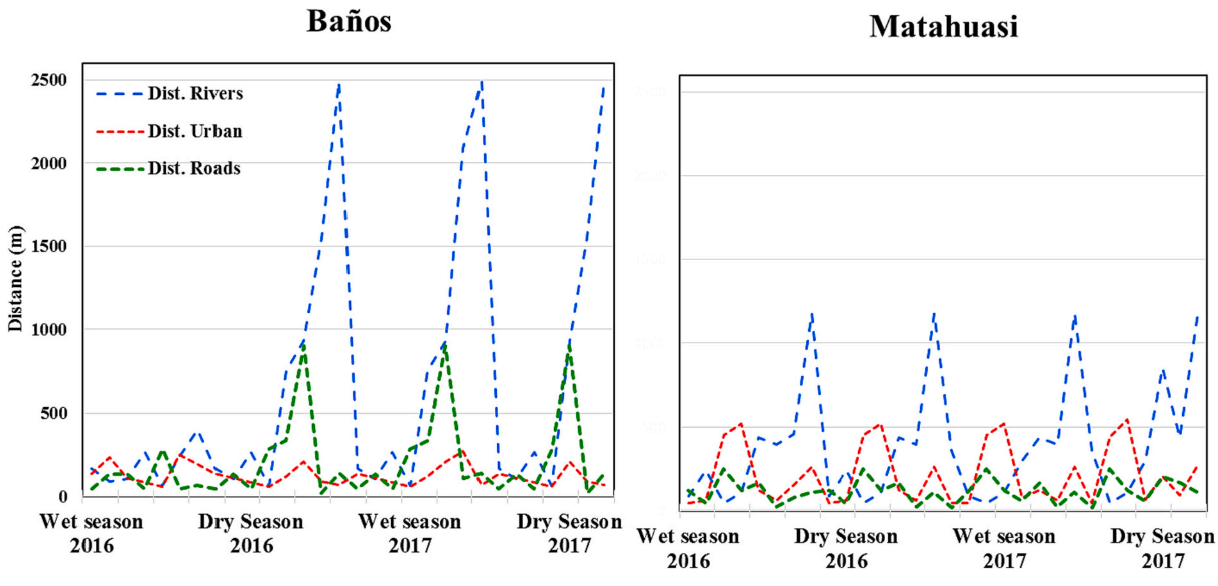

Fig. 4. Distance, in meters (m), to rivers, roads and urban zones from the geo-referenced grazing plots at the districts of Matahuasi and Baños during wet and rainy season (2016–2017).

seasons and 10.8% in rainy seasons, while those with low risk represented 4.7% in dry seasons and 12.5% in rainy seasons. In contrast, the 21.9% of the Baños area had a high risk of fasciolosis during the dry seasons and 12.1% during the rainy season. The areas suggested of moderate risk were 7.4% and 7.9% during the dry and rainy seasons, respectively. The areas identified as low risk by our model were >70% all year round in Baños (Fig. 8).

4. Discussion

Our study reports a novel model to map the spatial distribution of *F. hepatica* infection in dairy cattle at two districts of the Peruvian Central highlands, based on the levels of infection found and its relationship with environmental and climatic variables. Despite the

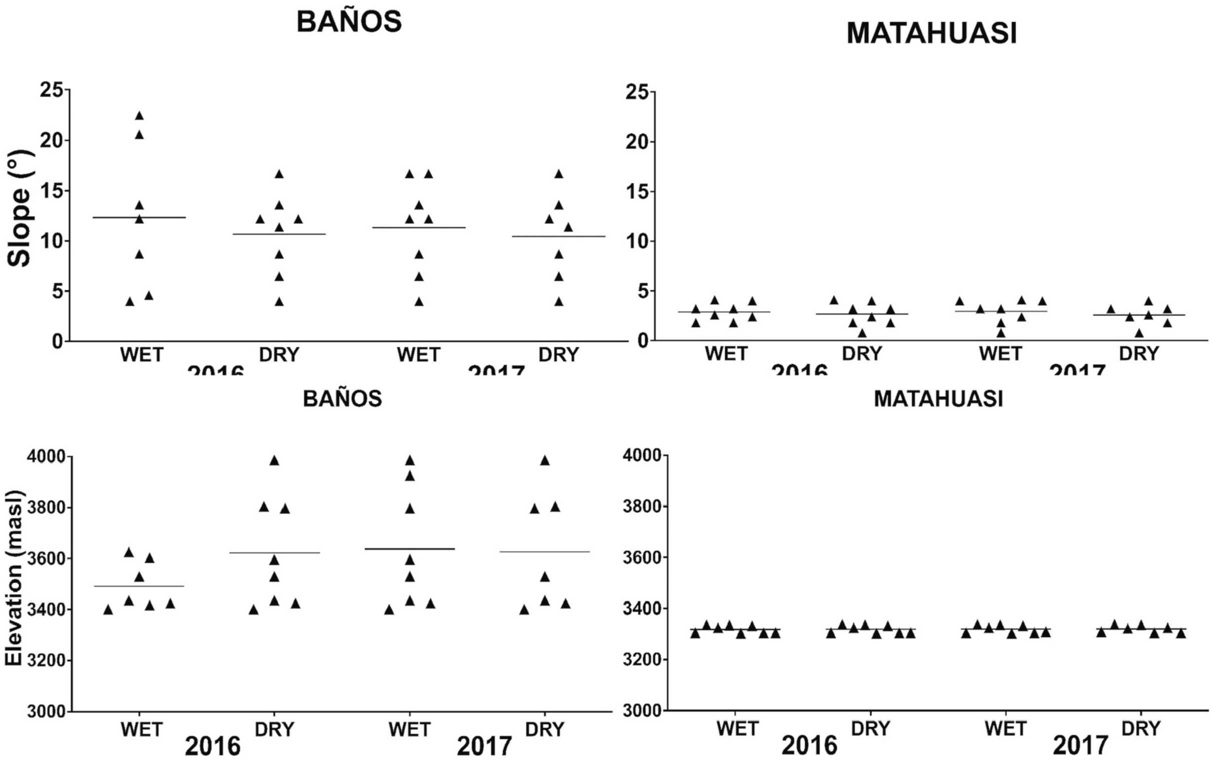

Fig. 5. Slope (°) (upper panel) and Elevation, in meters above the sea level (masl) (lower panel) from the geo-referenced grazing plots at the districts of Matahuasi and Baños during wet and rainy season (2016–2017). Each dot represents a herd sampled and lines represent the arithmetic average.

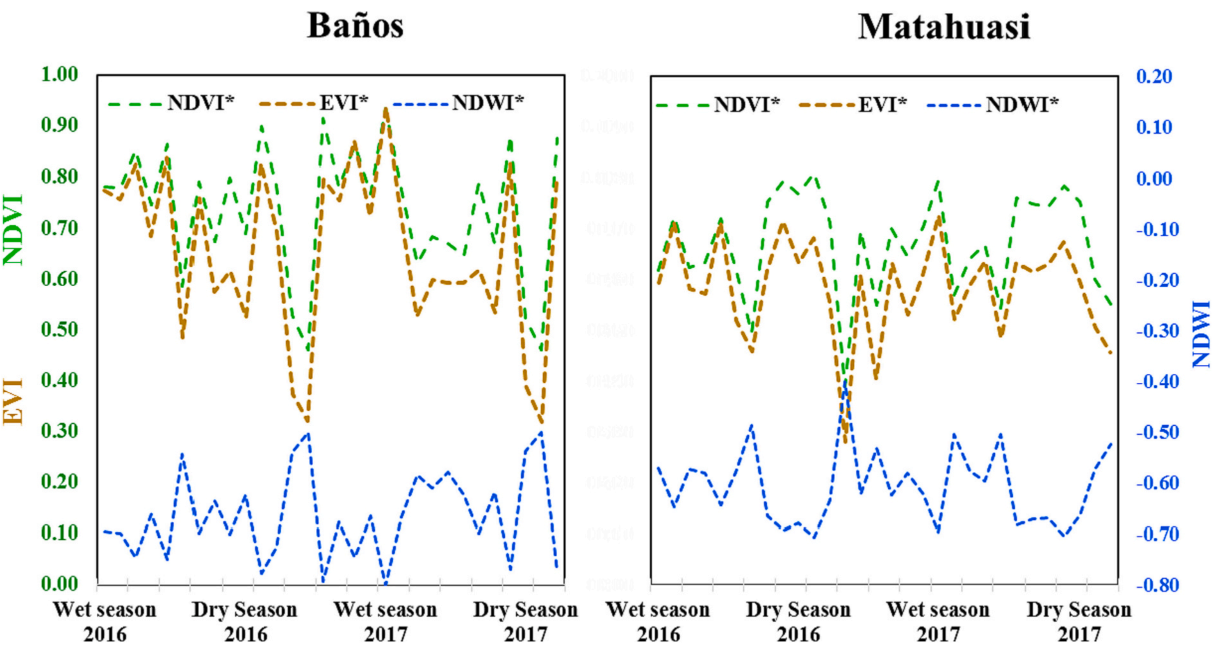

Fig. 6. Enhanced vegetation index (EVI), normalized difference vegetation index (NDVI) and normalized difference water index (NDWI) values from the geo-referenced grazing plots at the districts of Matahuasi and Baños during wet and rainy season (2016–2017).

Table 2
Concordance degree between observed and predicted *F. hepatica* risk according to cases processed by training (70%) and by testing (30%) the Artificial Neural Network model (ANN). Units are sampled animals (n = 61).

Example observed risk	Predicted risk			
	High risk	Low risk	Medium risk	Correct percentage
Training High risk (prevalence ≥50%)	30	1	0	96.8%
Low risk (prevalence <20%)	0	7	1	87.5%
Medium risk (prevalence >20% and <50%)	2	1	5	62.5%
Global percentage	68.1%	19.1%	12.8%	89.4%
Testing High risk (prevalence ≥50%)	8	0	0	100.0%
Low risk (prevalence <20%)	0	2	0	100.0%
Medium risk (prevalence >20% and <50%)	1	1	2	50.0%
Global percentage	64.3%	21.4%	14.3%	85.7%

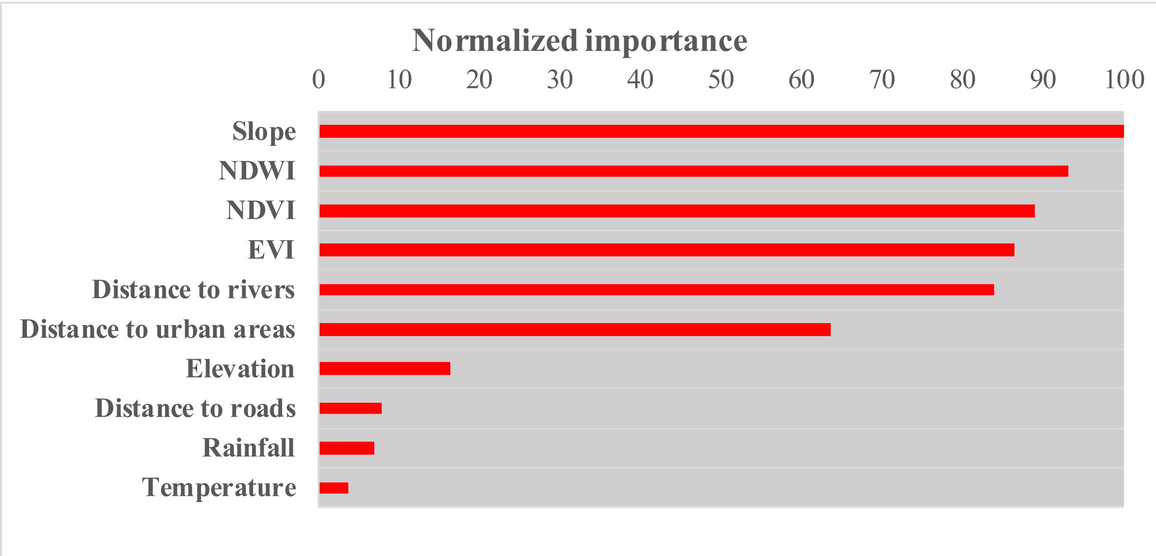

Fig. 7. Independent predictor variables according to the order of their importance in the predictive Artificial Neural Network model (ANN) developed for the districts of Matahuasi and Baños during wet and rainy season (2016–2017). EVI = Enhanced vegetation index, NDVI = normalized difference vegetation index and NDWI = normalized difference water index.

differences between them, both districts showed percentages in the range of others similar studies performed in the Peruvian highlands (Chávez et al., 2012; Ticona et al., 2010; Raunelli and Gonzalez, 2009). These previous studies also used coprological techniques to determine the prevalence of infection. Considering our sampling design and despite certain potential limitations, the two districts evaluated should be considered hyperendemic areas for bovine fasciolosis with moderate to high overall levels of infection all year round. These observations would contradict the historical dynamics of infection assumed to occur in the Peruvian highlands, with higher transmission rates during rainy season (Claxton et al., 1997). Therefore, in these districts, the parasite's life cycle develops all year round, including the dry season. One possible explanation for this finding is the wide use of flooding methods of irrigation in the grazing areas, especially during the dry season. This scenario would suggest that besides rainfall and temperature, other variables could explain bovine fasciolosis, such as slope, water and vegetation indices. These support the development of models to better explain the risk of infection in specific areas of the intricated mountain ecosystem prevalent in the Peruvian rangelands.

We have developed a model for fasciolosis risk based on an Artificial Neural Networks model (ANN) to assess the environmental factors that could best explain the presence of fasciolosis during the dry and rainy seasons. This methodology differs from other similar works, where other techniques, including statistical procedures, such as the Analytic Hierarchy Process (Freitas et al., 2014) or variants of machine learning, such as Random Forest or Boosted Regression Trees (Ducheyne et al., 2015). Although not commonly used for epidemiological studies on fasciolosis, ANN is also based on machine learning. Another difference in our methodology is the use of prevalence, categorized into three different levels, instead of positive vs. negative areas, as previously described in similar studies. However, the use of prevalence of infection, with a classification based on a threshold, has been applied to develop a climatic model for fasciolosis in Colombian dairy cattle (Vilhena Freire Martins et al., 2012). This precedent would validate our methodology to assess the variable of *F. hepatica* infection. The use of levels of infection was a decision made to better adapt the data to the ANN analysis.

The most important predictor variables in our model were slope, NDWI, EVI and NDVI. Regarding slope, the relationship between this variable and the risk of *F. hepatica* infection was inverse, since areas with steeper slopes had lower risk for fasciolosis. One possible

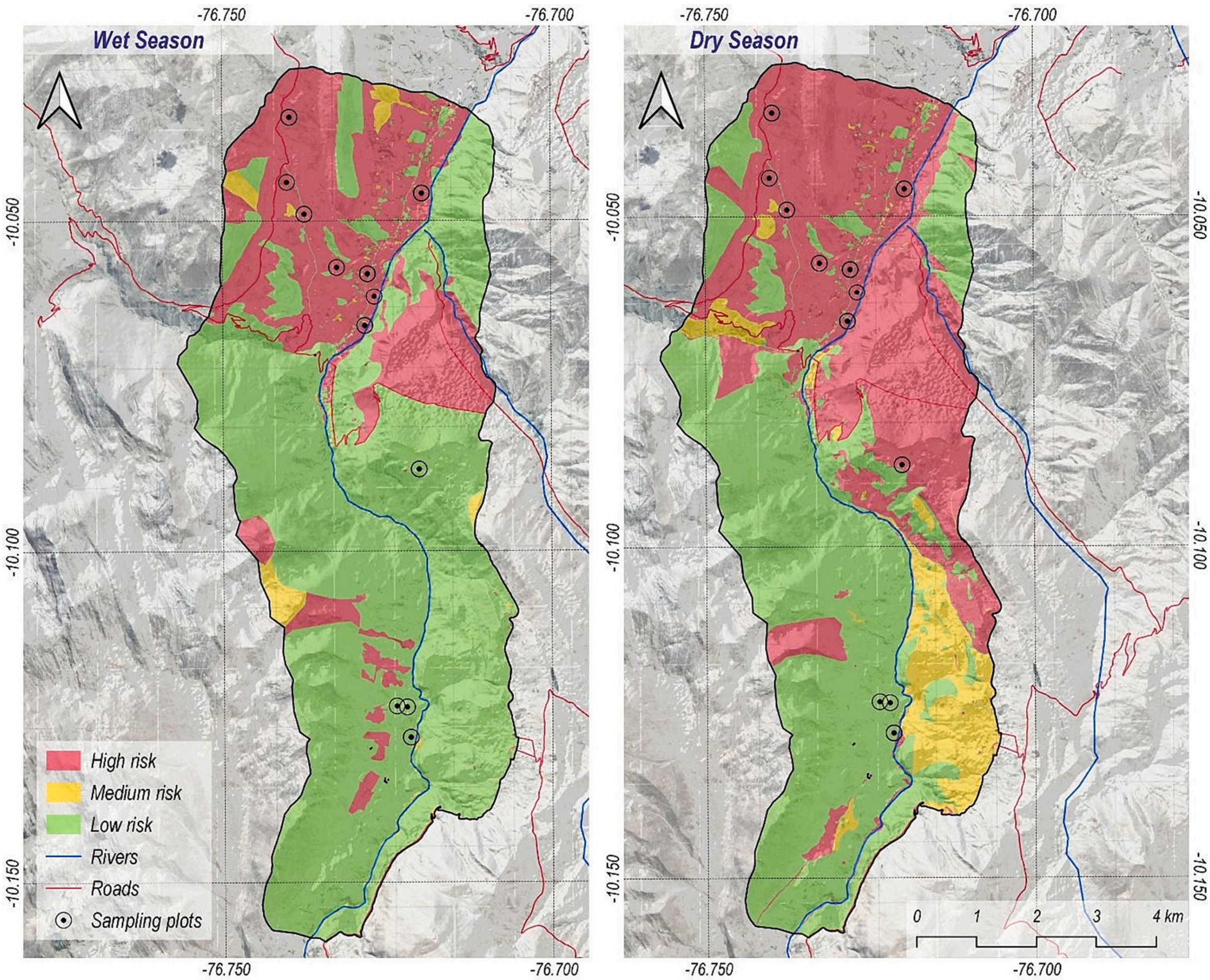

Fig. 8. Spatial distribution and risk, categorized in high (red), medium (yellow) and low (green), for bovine fasciolosis in the districts of Baños during wet and dry season (2016–2017). Sampling plot indicate the grazing plots included in the study. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

explanation for this would be that the steep slopes do not allow temporary bodies of water, reducing the proliferation of the intermediate snail (Malone, 2005; Mas-Coma et al., 2001). Slope differences could account for differences in the spatial distribution of fasciolosis in the evaluated districts, the Matahuasi slope reached a maximum of 26.9°, whilst Baños had slopes above 76.5°. Other studies on spatial modeling for bovine fasciolosis shared the concept of slope as a good negative predictor due to better drainage that would prevent the accumulation of water. This can be interpreted as a lowland vs. highland effect (McCann et al., 2010; Tum et al., 2004). On the other hand, Valencia-López et al. (2012) considered the slope as the third determining factor, after altitude and land use, within the epidemiological status of *F. hepatica*. However, it must be considered that this study was based on a theoretical model applied to a tropical coast region (East Coast of Brazil), a typical drier and warmer climate. Other reports have shown opposite results, indicating that slope is positively associated with *F. hepatica* prevalence, arguing that, in areas with higher slopes, there are surpluses of water that are collected in mountainous areas forming ponds and streams (Yilma and Malone, 1998) or that steeper slopes correlate with wet areas in low zones in a pasture (Bennema et al., 2011). One possible argument for explaining this contradiction is the differences in geographical and climatic conditions. These findings highlight the importance of performing epidemiological research in different zones of the vast mountain system of the Andean highlands where geographic and climate conditions could vary and this can impact the distribution of fasciolosis.

Vegetation and water indices were another important predictor variables in our model. These indicators, through remote sensing, can provide information on the state of vegetation (NDVI and EVI) and humidity (NDWI) for specific areas (Verhulst and Govaerts, 2010; McFeeters, 1996). NDWI was a positive predictor. This is considered to be efficient at detecting temporary water bodies. Taking into account that both are foci for the *F. hepatica* life cycle, NDWI should be pondered as a major risk predictor (Fuentes et al., 2001; De Roeck et al., 2014). NDWI has been reported as a key predictor of the risk at the farm level in the characterization of *F. hepatica* epidemiology (Qin, 2019) and it has been used for spatial analysis of distribution for other important parasitic diseases such as

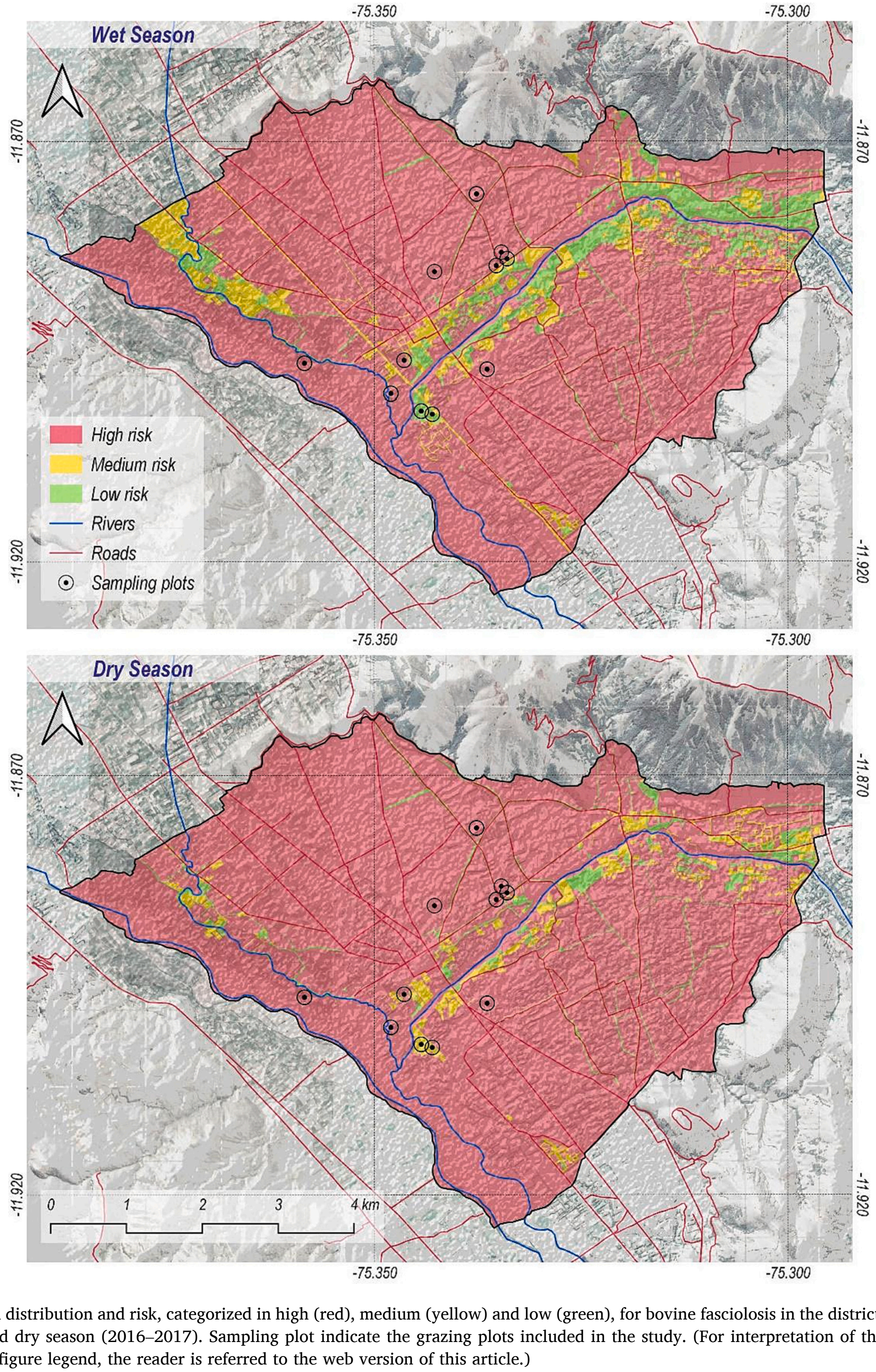

Fig. 9. Spatial distribution and risk, categorized in high (red), medium (yellow) and low (green), for bovine fasciolosis in the districts of Matahuasi during wet and dry season (2016–2017). Sampling plot indicate the grazing plots included in the study. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Schistosomiasis (Manyangadze et al., 2016) as well. Vegetation indices (NDVI and EVI) represent vegetation biomass; therefore, they can be used for determining pasture conditions (Durr et al., 2005; Wang et al., 2013). A high value on these indices represents better vegetation conditions that in turn indicate increased humidity (Huff, 2012). Based on these relationships, it could be assumed that the higher the NDVI and EVI, the greater the risk of fasciolosis. However, our model showed no correlation between NDVI and level of fasciolosis risk, therefore, other variables, such as slope or NDWI, could have a greater influence on the presence of fasciolosis in the evaluated areas. Selemetas and de Waal (2015) found similar results, with higher EVI and NDVI values in low-risk areas. Other studies have determined that the risk of transmission for *F. hepatica* is higher when NDVI values are >0.34 (Fuentes et al., 2001), while others have stablished a cut-off value of 0.45 (Fuentes and Malone, 1999). In our maps, average values were always higher than 0.49, in both districts, all year round. Therefore, these indices would indicate a permanent high risk of bovine fasciolosis. Various studies have considered vegetation indices as good predictors of fasciolosis transmission (Fuentes, 2004; Fuentes et al., 2005; Selemetas et al., 2015; Villa-Mancera and Reynoso-Palomar, 2019b) so they can be used for developing risk maps (Kantzoura et al., 2011; Raffo, 2013). However, our results reinforce the concept of NDWI being a better predictor of fasciolosis than the vegetation indices. This outcome could be due to the interaction of other variables or the particular characteristics of the Andean zones evaluated. Some authors have agreed with the idea of NDWI as a more appropriate index than NDVI or EVI for predicting fasciolosis (Wang et al., 2013; Gao, 1996).

Regarding elevation, this had low relevance in predicting the occurrence of fasciolosis. Other studies have indicated that the higher the altitude, the lower the degree of exposure to *F. hepatica*, since high soil evapotranspiration, low temperatures and mountainous areas would prevent the formation of water bodies (Kuerpick et al., 2013; Dutra et al., 2010; Bennema et al., 2011). However, in this study, the elevation in both Matahuasi (3300–3338 masl) and in Baños (3400–3987 masl), were considerably high. This outcome confirms the fact that *F. hepatica* has developed survival strategies in high-altitude Andean areas, which at the same time implies that the snail has also spread to those areas (Mas-Coma et al., 2001; Vilhena Freire Martins et al., 2012; Mas-Coma et al., 2008). In this context, the elevation of grazing plots in reduced areas of study, would not have major importance as a predictor of bovine fasciolosis.

One interesting finding of our work is that the prevalence of *F. hepatica* during dry seasons was higher than during rainy seasons, in both study areas. This could be because the changes produced by climate conditions in the spatial distribution of *F. hepatica* occur in the long term (Bennema et al., 2011). Therefore, minimal changes within small areas can be expected. Similarly, Kuerpick et al. (2013) found a low association between climatic variables and the prevalence of *F. hepatica*, with other factors being predominant. In contrast, other studies have found these variables as key factors for explaining the spatial distribution of bovine fasciolosis (Mas-Coma et al., 2008; Ducheyne et al., 2015; Rinaldi et al., 2015). However, these studies have developed models for much larger areas (country or even continent level) for periods of several years. This differs from our work, at a district scale and with reduced data at specific times, for only two years. Regarding differences from other similar studies conducted in the same region, Fuentes et al. (2005) developed a prediction model for human fasciolosis in the Mantaro Valley, showing that the wet season was the period of greatest risk of infection. Besides the use of a different host, humans, this study did not consider the interaction of weather with other multiple variables, such as vegetation and water indices, that allow the observed humidity in grazing plots, during the dry season. In this regard a major cultural factor not taken into account in our model is pasture irrigation by flooding, a very common cultural practice during the dry season in both districts, which maintain high levels of humidity in grazing areas even in dry periods. Irrigation of grazing areas constitutes a key factor for maintaining the life cycle of *F. hepatica* (Sangwan et al., 2016; Durr et al., 2005) because it would allow formation of temporary water bodies around grazing areas (Fuentes et al., 2001). The major influence of pasture irrigation on fasciolosis prevalence has already been confirmed for the Peruvian highlands (Claxton et al., 1997). Additionally, the melting of hail or frost, recurring phenomena during the dry seasons of the Peruvian highlands, could be the sources of moisture, as temperatures during the day at these times range between 15.9 °C and 1.9 °C (Briones Montero et al., 2020).

Although other factors not included in our analysis, such as cattle and pasture management, cattle density, the duration of the grazing period, grazing or cutting the grass to feed cattle, and grazing pressure (Raffo, 2013; Novobilský et al., 2015; Charlier et al., 2011) could have also influenced our results, this work confirms the utility of GIS and remote sensing in the development of risk models that explain the distribution and transmission of *F. hepatica* in cattle in the Peruvian Central Highlands. Even though our results should be interpreted cautiously, due to their specific limitations, they can be interpreted as a potential model to better understand the distribution of bovine fasciolosis in a specific region of the Peruvian central Andes. However, taking in account the geographical characteristics and the weather conditions of the Peruvian highlands, our results could be extrapolated to study bovine fasciolosis not only in other areas of the Andean highlands but in other endemic mountainous regions of high altitude around the globe. In this way, the professionals and producers involved could make decisions about the prevention and mitigation measures for hepatic fasciolosis according to their geographical location.

Declaration of Competing Interest

Daniel A. Zárate-Rendón reports article publishing charges, equipment, drugs, or supplies, and travel were provided by Flemish Interuniversity Council. David Godoy Padilla reports financial support and travel were provided by National Commission for Scientific and Technological Research National Fund for Scientific and Technological Development.

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