Modeling the correlation between late blight development and climate variables in
Cundinamarca, Colombia

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Abstract

The oomycete *Phytophthora infestans* is the causal agent of late blight, considered as the most important disease in potato crops worldwide. Due to this production relies on frequent fungicide spraying, increasing production costs, and eventually crop abandonment. Colombia is the third potato producer in Latin America. Therefore, we conducted this study to understand how weather influences the biological cycle of the pathogen in potato fields. For this, we described the climatic conditions of infected potato crops in Cundinamarca (Colombia) and calibrated, standardized and validated the GeoSimcast model for this region. The trial was conducted in twelve commercial potato fields in three municipalities of Cundinamarca. Lesion samplings were collected to estimate the number of sporangia and the proportion of the lesion in the leaf and began at the emergence of the crop in each field. We described the variability of climate conditions in long term throughout the department, also the relations between dispersal capacity (sporangia) of the pathogen and the weather conditions in each field. to check coherence with previous publications and assessed low threshold at 60 % of Relative Humidity for El Rosal with susceptible cultivar (sc) in 2009. With the new threshold and for susceptible cultivar we ran the GeoSimcast model to estimate the number of fungicides applications required to control late blight. The number of applications suggested by the model with 60% RH was very different from the real number but the model with 90% RH suggested a number more close to the real applications. In conclusion the farmers decided how much fungicide they have to apply assuming an optimal conditions (90% RH) for the all-seeding season. Therefore the numbers of fungicide applications suggested by the Model have to be validated in the fields to use the model as a base to make the seeding plan and make an optimal chemical management.
Keywords

*Phytophthora infestans*, late blight, GeoSimcast, weather, potato crop, sporangia, climate
Introduction

Colombia is the third largest potato producer in South America [1], but yield losses occur due to diseases and pests. Among these, late blight stands out. Caused by the oomycete *Phytophthora infestans*, late blight is a destructive potato disease (*Solanum tuberosum* and *S. tuberosum* group *phureja*) in the tropics and the most important pathogen of this species and other Solanaceous plants worldwide [2]. In Colombia, the first official reports of the disease were published by Toro [3] and Chardon [4] in the late 1920’s. Fungicides are the main strategy implemented to control the emergence and spread of the epidemic, but its extensive use highly increases production costs, and in some cases, causes crops abandonment in emerging countries [5]. For that reason, the development of resistant cultivars, as an alternative strategy for the control of this disease, is of great importance for farmers and researchers [6, 7]. Another research approach is focused on the development of innovative strategies for control of the pathogen in the field. This approach requires undermining the biology of the organism coupled to an ecological context, thus understanding the global variables that control the epidemic dynamics. Two concepts are key to contextualize this problem, pathogen reproduction and the effect of the environment on the pathogen fitness on the field.

Regarding the first, *P. infestans* presents both asexual and sexual growth. The asexual phase begins in the tube or in a foliage lesion, followed by production of zoosporangia and under optimum climate conditions direct germination, whereas in unfavorable conditions, zoospores are produced for indirect germination [8]. In Colombia, the sexual phase has not been reported yet and although Vargas et al. [9] detected the mating type A2, in addition to the already reported type A1, no sexual recombination has been conclusively yet demonstrated [10]. Weather conditions influence directly and indirectly the asexual phase of *P. infestans*. Temperature, for
example, has been shown to determine germination, i.e. at high temperatures infects by direct germination, and at low temperatures indirect germination [11, 12]. Humidity also has a major effect on the development of an epidemic on foliage of the potato plant because it determines two key stages in the life cycle of *P. infestans*; i) production of zoosporangia and ii) their germination leading to infection, on high humidity levels. Prolonged survival of zoosporangia and their formation also requires a high Relative Humidity (RH) [12, 13]. Rainfall as well, increases the availability of free water in the atmosphere, affecting the humidity and water on foliage surface. Without free water on the leaf surface, zoospores cannot be released from zoosporangia. Additionally, zoospores are unable to swim, and therefore infection cannot occur [11]. Also, under heavy rain conditions, spore dispersal is favored, as zoospores inside the droplet can be transported short distances within the plot[14]. The study of these variables in an isolated way can provide helpful insights on the possible behavior of the epidemics. However, interaction effects of these features may be influencing the local conditions in the fields, thus affecting the pathogen behavior. Modeling the pathogen behavior based on weather considers its main features: Rainfall, temperature, solar radiation and their interaction, relative humidity (RH), dew point and others. With the continued measurement of these variables, it is possible to calculate the historical trends, thus describing the long-term behavior of these variables. Any meteorological parameter that moves away from the historical mean is called an anomaly [15]

Computational models attempt to describe and predict the epidemiologic behavior of *P. infestans*. Model complexity has increased over the past years. Two types of models are of particular relevance; one type simulates and evaluates the disease in each stage, meanwhile the forecast model tries to predict the start of the disease and the critical epidemic stages through the seeding time[5]. The development of LateBlight[16, 17], BliteCast[18] and SimCast[19] models
allowed integrating variables that affect the disease establishment, development and propagation, to evaluate new management strategies and to evaluate the epidemiologic behavior. Some features considered were: host resistance, periodicity and fungicide type, severity, initial inoculum, rainfall, temperature, among others [20]. Models as LateBlight and SimCast are forecast models, and were designed to predict the fungicide scheme according to weather conditions (relative humidity, rainfall and temperature) and disease time [5]. Novel models such as GeoSimcast, developed by CIP (International Potato Center), integrate numeric description of the epidemic (i.e severity curves), climate range and host response [21]. Fungicide schemes can also be considered. The model was developed in Java Runtime Environment and makes use of SimCast variables in a forecast model, as a novel feature. The final output can be visualized in a Geographic Information System (GIS) environment.

These models rely on recurrent patterns of weather along the year, e.g. rainfall distribution. Those patterns are then an important factor on the development of unaccounted rapid spread epidemics. In some cases nonetheless, climatic patterns do not comply, in the Andean region for example; when trade winds push warm surface waters of the Pacific Ocean from east to west. Current generates an accumulation of warm water in the western Pacific and in the South American coast an upwelling zone. This ocean current is called the Humboldt Current. As a consequence of the weakening of i) the Humboldt current, the flow of the surface warm water from east to west is reversed and ii) the upwelling zone; generated ENSO (El Niño Southern Oscillation) phenomenon, a very important climatic anomaly [15]. Consequently the surface temperature of the ocean increases in western South America, affecting air temperature, rainfall and river flow. The opposite phenomenon is called La Niña, characterized for lower than average temperatures in the surface waters of the eastern Pacific Ocean because the Humboldt
Current becomes stronger and the upwelling zone increases [15]. According to the official communication of IDEAM (Instituto de Hidrología, Meteorología y Estudios Ambientales), which is based on NOAA (National Oceanic and Atmospheric Administration) (EU) and ECMWF (European Centre for Medium-Range Weather Forecasts) predictions of climate anomalies, in Colombia the last El Niño phenomenon began in 2009 and had a moderated impact until the first four months of 2010 with a harder impact in the amount of precipitation throughout the country, that could be in excess or deficit of rainfall according to the zone [22-24].

In order to integrate the aspects that influence the beginning and the progress of late blight in potato fields, the objectives of this study are i) to monitor and describe the epidemic in three different municipalities and cultivars, in terms of dispersal potential (number of sporangia) and disease progress (foliar area of the lesion), ii) to describe the influence of weather on the dispersal potential; iii) to calculate the threshold of relative humidity (RH) in which the production of sporangia increases; iv) to run GeoSimcast with the calculated thresholds and compare with the real number of fungicide applications.

Materials and Methods

**Sampling sites**

Late blight surveys and samplings were performed from 2009 to 2013 in several locations in three municipalities of Cundinamarca, Colombia: El Rosal, Subachoque and Facatativá (Fig 8, Table 1) with the agreement of growers, field owners and assigned agricultural extension agents of Federación Colombiana de Productores de Papa - FEDEPAPA (National Federation of Potato Producers). The fields were chosen according to the following criteria: i) varieties grown and ii) days after emergence (i. e. days after germination). Due to the commercial crops usage,
fertilization and commercial fungicides and pesticides were applied according to the standard grower-practice in each region. We sampled several potato (Solanum tuberosum and S. tuberosum group phureja) cultivars, such as, Diacol Capiro (R-12) (susceptible), Pastusa Suprema (resistant), Criolla Colombia (moderately susceptible) and ICA Única (moderately resistant) (Table 1). Tuber seeds were planted in different months according to the region and the year.

**Disease progress curves of epidemic of Phytophthora infestans and Climate effect over the epidemics.**

Late blight lesion samplings were made at the beginning of the crop emergence process according to the day in which the field was planted. We defined two transects within the plot that displayed representative coverage of the field, between 6 to 9 samples were collected in each location per point of time (Suppl. Table 1). A sample consisted of ten leaflets, these were placed into a 50 ml sterile tube with sterile water. Sporangia counts were performed in duplicate using a hematocytometer. These data was used to evaluate the dispersion capacity of the pathogen over time. Additionally from each leaflet the lesion area measured to calculate the severity by AUDPC (Area Under Disease Progression Curve) and rAUDPC [39].

To assess the relationship between meteorological variables and epidemic propagation variables (e.g.: amount of sporangia), we used several linear models in R v. 3.0 [26] and Granger correlations based on time shifts in some cases [27] to fit the climatic data (see below) and the sporangia counts. The usage of the climatic information allows us to know the weather dynamics for each station.
The influence of climatic variables was determined evaluating nine linear models using the Akaike Information Criterion (AIC). Models include the relation between sporangia counts and each variable or combinations of variables.

**Data assessment and systematization**

The spatialization of the weather stations, that belong to the national catalogue of CAR (Corporación Autonoma Regional) and IDEAM (Instituto de Meteorología y Estudios Ambientales de Colombia) institutes, was computed using ArcGIS [25] to select the nearest stations to the collection fields. Daily climate data from 66 stations were provided by IDEAM (agreement 018/2011) and data from other 12 stations were provided by CAR (Fig 8). The data was systematized in a relational database using MySQL database manager. The database consisted of 5 tables; four tables summarize the information of four climatic variables: i) Rainfall, ii) Relative Humidity, iii) Maximum Temperature and iv) Minimum Temperature for every day of the selected years.

A relational table contains information related to the stations such as geographical coordinates: Latitude, Longitude and elevation. This new table was linked to the previous tables, having as result that for any given station its geographical location and climate variable can be easily retrieved. Data interpolation was performed to determine the climatic behavior for each area of study (see below). These data was included in a table linking climatic data and spatial information.

**Climate data; Analysis and Processing**
Multiannual climate analysis was made using data from CAR and IDEAM databases; monthly data was selected using the following criteria i) More than 500 m from a water body, and ii) data records over 30 years. As a result, 43 stations were selected for rainfall data and 18 of the selected stations included variables related to humidity and average temperature. To determine long term patterns in climatic variables we performed a multiannual analysis of data over a 30 year period in the selected area. In order to complete the multiannual climate analysis, missing data was interpolated using average values of the same variables for latter years. It is important to remark that a multiannual table was calculated for every month of the year.

For this analysis we took into consideration only stations for which variables such as rainfall, relative humidity and average temperature were available; to illustrate the behavior of the overall features, we plotted simultaneously average temperature, rainfall and relative humidity in a chart where an axis represents the scale of temperature and rainfall A and another axis represents relative humidity B. This was useful to exemplify the relationship between the variables necessary to describe the climate conditions of each site. It was possible to create a map using the georeferenced data provided by the CAR and IDEAM in order to be able to select the most representative stations. This map was processed using ArcGIS and the anomalous years were selected according to the severity classification of IDEAM’s *Atlas Climático* (Climate Atlas) [15], which helps to determine the beginning and the ending of the anomalous years.

Our model requires nonetheless, more information to trace the behavior of the weather variables for the sampled fields. To generate this we used an interpolation method, using the computer software ANUSPLIN [28]. This software is based on spline models and allows the allocation of data over a geographical surface. Using the SplineA console we assessed each station as a data point, the regressor variables considered are the meteorological features to be
evaluated (e.g: rainfall) geographical coordinates (e.g: latitude & longitude) and the altitude in meters over the sea. The model extracts, by location, the climate conditions across the 3-years period according to the sampling time. The estimated surface represented data in a grid of 85 rows and 74 columns. The output files were given in ASCII format, where the header describes the area of the surface and the number of points of the grid. These files were converted to RASTER format using model builder in ArcGIS v 10.1. After that, the daily climate data of each field was extracted from the weather surface.

**GeoSimcast**

GeoSimcast is a program based on Java programming language [29]. This program combines an algorithm to obtain Simcast variables and run Simcast forecast model over a weather surface data. The weather surface is coded with a matrix of numbers representing colors (number of fungicide applications during each year) and coordinates. In GIS, these weather surfaces or matrices of data are known as a raster or grid, based on geographic information, and could be visualized as agroclimatic risk maps.

Simcast is a forecast model used in potato late blight disease [18] which can help to predict the timing to spray fungicide in potato crops. As a daily data it uses three weather variables: number of hours above a humidity threshold, temperature during the same time period, and rainfall. The first two variables point out the disease severity as blight unit (BU), and the rainfall amount is related how much of active ingredient is washed from the leaves and it is represented as fungicide units (FU). After an accumulated threshold of BU or FU the model indicates the timing of sprays.
Results

*Climatic conditions and disease*

**Different climate conditions found throughout the Department**

The Eastern Cordillera goes across the department (Fig 8), with two clearly distinguishable rainfall regimes. We found it to be monomodal on the Eastern slope of the Cordillera, as revealed by two stations Saucio and El Consuelo, whereas the Cundiboyacense plain and Western slope were characterized by a bimodal regime. Bimodal regimes had the first peak between April and May, while in the second semester the peak was between November and December; the months with the lower amount of rainfall were February, March, June and July. The relative humidity was similar though the Department and had the same behavior as rainfall (Fig. 1).

The relationship between different climate variables was determined from the multiannual analysis. Relative humidity and average temperature, showed a bimodal behavior but in different periods of the year (Fig. 2), this is similar to the rainfall regime. The climographs for weather stations depicted long-term climate conditions and the interaction between the variables. For example, relative humidity and temperature, in the majority of the stations, were correlated. On the other hand, in Tabio station, both, temperature and rainfall, increased. This correlation was also clear in the stations on the Cundiboyacense plain near to the Eastern slope.

**Anomaly conditions**

We found differences in rainfall during normal and anomalous seasons; a comparison was performed between the multiannual calculation and the values from the years when the anomalies occurred. The severe years reported by IDEAM were used: from May 1997 to May 1998 for El Niño and from May 1988th to March 1989th for La Niña [15].

The Eastern slope showed a monomodal regime with a peak in July. During El Niño phenomenon there were several moderate peaks in March, May and October, followed by five months with less
rainfall. During La Niña phenomenon there were three peaks through the year, the first was in March as in El Niño phenomenon, the second was moderated in July and finally in October-November a higher one (Fig. 3). El Niño phenomenon showed a concentration effect of the rainy season in two months thus generating less rainfall in the next eight months, while La Niña phenomenon sharpened the season in four months that presented less rain than the rest of the year (Fig.3). In the Western slope under El Niño phenomenon, the rainy season concentrated in the first semester of the year, leaving the other seven months with less amount of rainfall; opposite to La Niña phenomenon that concentrated in the second semester of the year with some exceptions that moderated the dry season.

Sporangia curves as a dispersal measure of disease

The overall behavior of the sporangia dispersal was different for each of the sampled fields. Differences were observed in the sporangia curves, on the initial amount of sporangia (IAS) and the trend of the curve. The highest value for IAS was 68,125.00 sporangia/ml for R12 a susceptible cultivar sampled in 2009, followed by B1 with 47,638.00 sporangia/ml for moderately susceptible cultivar sampled in 2013; the lowest value was 138.88 sporangia/ml for SC a resistant cultivar sampled in 2013. The increased tendency of the epidemic in Facatativá with one, two or three peaks showed a zigzag behavior through time (Fig. 4). The curve with the lowest sporangia values and slopes between sampling days was B1, while F field had the highest ones. In El Rosal the epidemic curves did not show a clear trend, but the Criolla curves had the lowest values while the R-12 cultivar sampled in 2009 had the highest ones. In the case of the fields sampled in 2012, both cultivars showed an opposite behavior, the R-12 cultivar had an increased tendency; meanwhile the initial and final values of severity were higher for the cultivar Unica (Fig 4).

Climate conditions and their effect on the sporangia curves
Significant correlation between weather variables and the behavior of the epidemic was found. The amount of sporangia per field was influenced by the relative humidity, maximum and minimum temperature, being maximum temperature the variable with the greatest explanatory power over data variation, showing low sporangia counts for high temperatures (Fig 4). Linear correlation was found. A regression model considering these three variables as drivers of disease dispersion, showed the lowest AIC in comparison to other 7 models that considered different sets of weather variables. Data for the years 2009 and 2012 was fitted using this model. For 2009 and the cultivar R12 the best model included data from the day before sampling (p-value = 0.02**, R = 0.9365); for 2012, potato cultivars Criolla and Unica the model used data from the sampling day (p-value = 0.21, R = 0.8524 and p-value=0.049*, R = 0.9667); finally, for 2012 and cultivar R-12 the best model included data from two days before sampling (p-value =0.1818, R=0.8748).

Sporangia curves for 2009 showed the highest amount of sporangia, and this correlated with the lowest values of minimum temperature as observed in Fig. 4. The highest minimum temperature accompanied the next decrease in the curve. In 2012, for cultivars R12, Unica and Criolla curves showed moderated changes in temperature and low rain values (Fig. 4).

**Severity progress curve**

To determine the relationship between meteorological conditions and disease establishment, we estimated disease progress curves (DPC) and rDPC for each field. We found differences among the different cultivars and locations (Fig. 6a). Differences are confirmed by the area under the curve AUDPC and rADPC (Fig. 6b and 6c). The fields located in Facatativá showed higher severity values in comparison with the other locations. The four fields of Criolla cultivar showed a zigzag behavior with an increasing trend in severity, with a final decrease at fields B1, B2 and B3. The F field differed from the other three in the same location, as it did not show any reduction in the disease progress (Fig. 5a). Higher AUDPC and rAUDPC values were observed from fields in this location; with the highest AUDPC value for B1 field and the highest rAUDPC value for F field. For El Rosal, two different cultivars were sampled,
these cultivars depicted differences in resistance level for two different cultivars (Criolla for RC field and Suprema from Rce). The epidemic appeared late in the season for both cultivars; DPC showed an increased behavior for Rce, while few incidence was found in RC field. Additionally the higher value of AUDPC and rAUDPC were from RC field. SC and SM fields, from Subachoque location, showed no incidence and the lowest incidence frequency respectively (Fig. 6b and 6c). The AUDPC and rAUDPC are consistent with the lower incidence for both fields.

**GeoSimcast analysis**

Agroclimatic risk map showed the disease severity in the area. Risk is represented by the number of fungicide applications in the seeding time, necessary to control the epidemic, in this analysis two different types of cultivars were considered one with high resistance and other with high susceptibility, also two different thresholds 60% and 90% of RH (Fig. 7). The distributions of the predicted zone by the model were the same for each threshold and apparently the cultivar influenced the amount of fungicide to control the epidemic. Applications ranged from 1 to 8 applications by resistance cultivars in the sampled zone, this is consistently different with the data found in the fields (7-14 applications) with susceptible and moderately susceptible cultivars. The model with 90% RH (Fig. 7-left) showed a similar number of applications for each cultivar respectively, however the distribution pattern of the applications changed significantly, as two different zone are clearly distinguished for the Subachoque and El Rosal fields. In these selected fields different fungicide regimes can be distinguished, different municipalities show different propensities to infection. During the seeding time the fields of Subachoque had an average of 12 to 14 applications on contrast to 4 to 9 predicted by the model for 60% RH, but the model with 90% RH predicted 10-13. The predictions for Rosal behaved different from that of Subachoque and standard applications (7 to 8) with a regime of 0 to 3 applications and 0 to 10 according to the 90% RH model. Finally for Factativa we estimated a requirement of 1 to 2 applications and 10 to 13 by the model with 90% RH; meanwhile the commercial growers applied a total of 10-14 on the overall season (Fig XB,
Table 1). However the estimated regimes are consistent with the clear differentiation of climatic characteristics between Subachoque and the other municipalities.

**Discussion**

This is the first study to follow the weather variables in commercial and large potato crop fields, thus exploring climate influence over late blight disease in Colombia. The limited availability and quality of data, compared to laboratory and greenhouse studies [5, 13, 16, 17, 21, 30], makes of this study a challenging work. Climate data collection is poorly centralized and automated in Colombia; so, it is of high relevance to evaluate epidemic models sensitivity to the particulars of these data. The field has a myriad of different features that provide researchers with large sets of heterogeneous data, such as different cultivars, locations and weather conditions. The generation of agroclimatic risk maps allows adequate territorial planning, knowing the long-term patterns, it is possible to estimate the state of the weather variables in the seeding period, this coupled with the calculation of the optimal weather states for the spread of the epidemic [31], could serve as an applied tool for crop development, thus helping to establish bridges between academy and farmers.

The study zone is placed in the west slope of the Eastern Cordillera. For that reason all the stations showed a bimodal precipitation behavior, having more rainfall in the first part of the year, a dry period in between rain seasons with duration of up to four months, consistent with the establishment of dry and wet season regimes in Colombia [15]. Temperature did show rather a small variation across the year and the locations. On the other hand, values of relative humidity were higher in Subachoque and Facatativá than in El Rosal, for the neutral year (2012 and 2013). This effect was accentuated during the El Niño phenomenon (data not shown). We propose that through the use of global climatic features (season recurrency), particular periods of sensitivity to infection can be properly determined, as well as changes of epidemic behavior in anomalous seasons.
Our hypotheses, on the correlation between weather features and the spread of the disease were tested using linear models to fit sporangia curves and variables such as temperature, rain and relative humidity. Temperature and solar radiation have been proposed as key factors in the development of the disease. It was possible to predict a relation between the climate variables and sporangia counts for each field. In the sampled fields there was a variation between 60 and 90% relative humidity and 15 - 22 ºC values for maximum temperature, those values correspond to high humidity and low temperatures that were correlated with low solar radiation [32] and largely explained the variability of the data. Nighttime is important in the dispersion because low temperatures are required for sporangia release. Low temperature data could be useful to determine which periods of the year present more risk of disease outbreak [32-35]. Interestingly we found that time lag of these variables had has a very significant effect on the response. This fact had also been addressed in previous studies, and is of great importance to think in the delayed effect that these variables have over the pathogen development and proliferation [36]. Solar radiations explain variation in sporangia counts, as solar radiation increased risk for disease outbreak [34]. However this variable was not considered on our study and should be included in future studies.

Climate variability throughout the department and sampled fields affects late blight incidence in the potato crop. The dispersal of the sporangia depends on environmental conditions, zoospores lack specialized structures for survival, thus being susceptible to drying and solar radiation. However, sporangia are produced in large amounts on infected plant tissue and can be carried by wind to new locations [33]. Favorable environmental conditions for dispersal are cool temperature (15 to 22 ºC) and high humidity (95 to 100%), which is observed in the sampling fields from seeding time until harvest. Infection cycles of the pathogen showed a zig-zag pattern with continuous increase and decrease in the amount of sporangia over time, this is consistent with aspects of its biology that determine reproduction waves over infection times [32]. The resistance of cultivars also affects the colonization of new plants: between cultivars R-12 Diacol Capiro (susceptible) and the other cultivars (medium resistance) there is a difference of ~30000 sporangia/ml when comparing highest counts for each cultivar. Sporangia curves showed differences between fields that could be correlated with weather conditions and cultivar resistance.
In addition of sporangia data, we decided to quantify the resistance of the analyzed cultivars by measuring the lesion area on the leaves. All fields showed a progress epidemic through time, with two fields with short peaks. The beginning of the crop season in each field was according to the climate conditions, for Facatativá the planting time was in a wet season and in El Rosal or Subachoche was in a dry one. However, the differences among the cultivars were shown by the proportion of the lesion area in a susceptible cultivar such as Criolla vs a moderate resistant cultivar such as Suprema. In conclusion we found differences in the AUDPC and rAUDPC values related with the susceptibility/resistance of the evaluated cultivars.

GeoSimcast (Fig. 7) model showed that, for 90% RH, resistance and susceptible cultivar in 2009, our fields were divided into two different zones. Subachoche fields and few in Facatativa, were more susceptible to the disease than Rosal field, which are represented by a major number of fungicide applications for Subachoche (6-8/18-21 applications), while the number of applications is 12-14 by the local farmers. This is correlated with the climate because it was an anomalous year. During the first semester, there was a moderated rainfall peak, and after June initiates a dry season, so the sporangia decreased until crop end, and it was not necessary to apply more fungicide [15]. The model suggested less application by the 60% RH model and more applications for the 90% RH model to the commercial crops used to use, however, the standard management in that location did not take into account climatic variability in the year and the similarity with the second model is because the farmer assumed a constant optimal conditions for the pathogen throughout the season, also the anomalous periods and are supposed to be useful for the worst conditions.

Variations between model and standard commercial practices in the fields could be also correlated with experimental conditions; experiments used to calibrate and validate Simcast models are often done in small fields and standard conditions in lab [5, 13, 16, 17, 30, 37]. These studies do not account for the role of environmental variables in large fields, nor fields with the different cultivar along the area. This is the first work to include commercial crops data to calibrate the GeoSimcast model. Sampling across three years, provided us with the variability of climate in planting times through the
year. SimCast models for severity take into account several microclimatic factors, which are difficult to measure in the field. The estimation of these factors from global climatic variables, using GeoSimcast, enabled us to calculate severity of the infection. This assessment allows the test of microclimatic dependent factors in the infection, such as the DPC. Model predictions and performance of cross-validation with field data expands the horizon of environmental dependent infection patterns [37].

*P. infestans* sporangia curves and climatic variables can be used in predictions of late blight on potato tubers and for better disease controls. Hypothesis testing on the field largely enables the formulation of useful recommendations for the optimal use of fungicides in each field. To obtain an accurate predictive model for Colombian crops, sporangia curves should be measured under a broad range of environmental conditions, locations and include solar radiation data in the analysis. Also, quantitative knowledge of the survival and spread of *P. infestans* sporangia is important to understand and manage late blight in commercial crops. The application of short and long-term climatic models can enable the prediction of epidemic dynamics that integrated in agro-climatic epidemiology could be very useful tool to applied agriculture. The conjunction of agro-climatic models (GeoSimcast) and climatic models such as CCCma models [38] could provide us with venture features for the new distribution and interaction between the plant and the oomycete, and also the consequences of actual standard practices over the number of fungicide applications.

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References


Figure 1. Multiannual Rain regime in Cundinamarca 1969-2009. The x-axis of the charts represents the month in numbers and the y-axis the amount of rain in mm.

Figure 2. Multiannual calculations of Mean Temperature, Rain and Relative Humidity in Cundinamarca 1969-2009. (a) Annual rain regime for different meteorological stations in the study zone. (b) Annual relative humidity for different meteorological stations in the study zone. Data shown for 15 years, Blue: Average Monthly Data, Green: Maximum Monthly Data, Red: Minimum Monthly Data.

Figure 3. Comparative charts between the multiannual means and true year of El Niño/La Niña phenomena.

Figure 4. Sporangia curves of late blight pathogen based on the samplings in different locations and cultivars, during 2009 and 2012. Climate conditions are depicted.

Figure 5. Sporangia curves of the late blight pathogen based on the samplings in different locations and cultivars during 2013. Climate conditions are depicted.

Figure 6. (a) Late blight disease progress curves in three locations (Facatativa, el Rosal and Subachoque); (b) AUDPCs for each field; (c) rAUDPC for each field. Colors represent fields for each location.
Figure 7. Risk Map for three municipalities (Rosal, Facatativa and Subachoque) in anomaly weather conditions, for a susceptible and resistance cultivar during the seeding time and threshold of 60% RH (Right of the graph) and 90%(left of the graph).

Figure 8. Map with stations and sampling fields
Figure 1
Figure 2
Annual Rainfall Average (%) (mm)

Figure 3
Figure 4
Figure 6
Figure 7
Figure 8.
Table 1. Locations and fields selected for the study, years of collections, fungicide treatments, seeding time for each variety, late blight resistance, potato cultivars grown.

<table>
<thead>
<tr>
<th>Year</th>
<th>Field</th>
<th>Cultivar</th>
<th>Municipality</th>
<th>Latitude</th>
<th>Longitude</th>
<th>Fungicide treatment</th>
<th>Seeding time</th>
<th>Cultivar resistance *</th>
</tr>
</thead>
<tbody>
<tr>
<td>2013</td>
<td>B1</td>
<td>Criolla</td>
<td>Facatativá</td>
<td>4.9669</td>
<td>-74.2867</td>
<td>10-12</td>
<td>120 days</td>
<td>MS</td>
</tr>
<tr>
<td>2013</td>
<td>B2</td>
<td>Criolla</td>
<td>Facatativá</td>
<td>4.9589</td>
<td>-74.2917</td>
<td>10-12</td>
<td>120 days</td>
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* Level of resistance of a potato cultivar to late blight: S = susceptible, MS = moderately susceptible, MR = moderately resistant, R = resistant, HR = highly resistant.

** SimCast blight units as determined by temperature and periods of high relative humidity (RH) in the field.