SUB-COMPONENT STUDY: PRECIPITATION AND TEMPERATURE SHIFTS DUE TO CLIMATE CHANGE IN NORTHWEST QUITO CANTON, ECUADOR

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KEY MESSAGES

- Precipitation and minimum and maximum temperatures are likely to increase over northwest Ecuador over the 2020s (2010-2039), the 2050s (2040-2069) and the 2070s (2060-2089).
- Precipitation and minimum temperatures are likely to increase more in the dry season than the rainy season, but will still increase in the rainy season.
- These changes may create more favorable climate conditions for some disease-carrying vectors like mosquitos and sand flies.
- Other factors, like land-use change and human behaviors, will also influence the spread and life cycle of vector-borne diseases. These factors were investigated by the other collaborators to the overall study.

Sub-Component Study: Precipitation and Temperature Shifts Due to Climate Change in Northwest Quito Canton, Ecuador

– for –

Climate Vulnerability of the Health Sector in Quito: Making Technical Data Accessible to Policy Makers

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Acronyms

AR5	Fifth Assessment Report
CDF	cumulative distribution function
CMIP5	Coupled Model Intercomparison Project Phase 5
CRU	Climate Research Unit of the University of East Anglia
ENSO	El Niño Southern Oscillation
FAE	Fuerza Aérea Ecuatoriana
GCM	General circulation models
GFCS	Global Framework for Climate Services
GHCN	Global Historical Climatology Network
INAMHI	Instituto Nacional de Meteorología e Hidrología
INOCAR	Instituto Oceanográfico de la Armada de Ecuador
IPCC	Intergovernmental Panel on Climate Change
ITCZ	Intertropical Convergence Zone
MDQ	Metropolitan District of Quito
MedEns	multi-model mean
NCEI	National Centers for Environmental Information
NNPG	Nanegal, Nanegalito, Pacto and Gualea parishes
PCMDI	Programme for Climate Model Diagnosis and Intercomparison at Lawrence Livermore National Laboratory
PDO	Pacific Decadal Oscillation
QCCS	Quito Climate Change Strategy
RCP	representative concentration pathways
RSME	root-mean-square error
TRMM-TMPA	Tropical Rainfall Measurement Mission-Multi-satellite Precipitation Analysis
VBD	vector-borne diseases
WMO	World Meteorological Organization

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1. Introduction

Ecuador has diverse populations, cultures and economic sectors spread in a broad rural to urban continuum. It is also a country with a multitude of highly specialized ecosystems, such as the mountain páramos to varied forests, and significant biodiversity. Both the human and environmental continuums are strongly shaped by the country's complex topography, as are the vectors (e.g. mosquitoes and sand flies) that contribute to some diseases, like dengue or zika, in various parts of the country. Many disease-causing vectors require specific meteorological and habitat conditions at various stages of their life cycle. For example, ambient temperature and humidity are important considerations in the development and survival of larval and adult mosquitos; shifts in weather conditions influence vector range and life cycles, and disease transmission.

The IPCC 5th Assessment Report states with *very high confidence* that the health of human populations is sensitive to shifts in weather patterns and other aspects of climate change (Field et al. 2014). Assessments of the health impacts of climate change are beginning to focus on acute effects that can be approximately quantified, such as vector-borne risks or heat stress among workers (Githeko et al. 2000). The range and lifecycle of many-disease causing vectors—e.g., mosquitos, Triatominae bugs, or sand flies, among others—are likely to shift in the future due to a number of factors. Some factors include: land-use change and increasing development of forested areas; increasing human travel and trade along improving transportation networks that facilitates the spread of vectors and disease; and, increasing variability and shifts in precipitation, temperature and other meteorological variables due to climate change (Moore et al. 2012; Li et al 2010a; Reiter 2001).

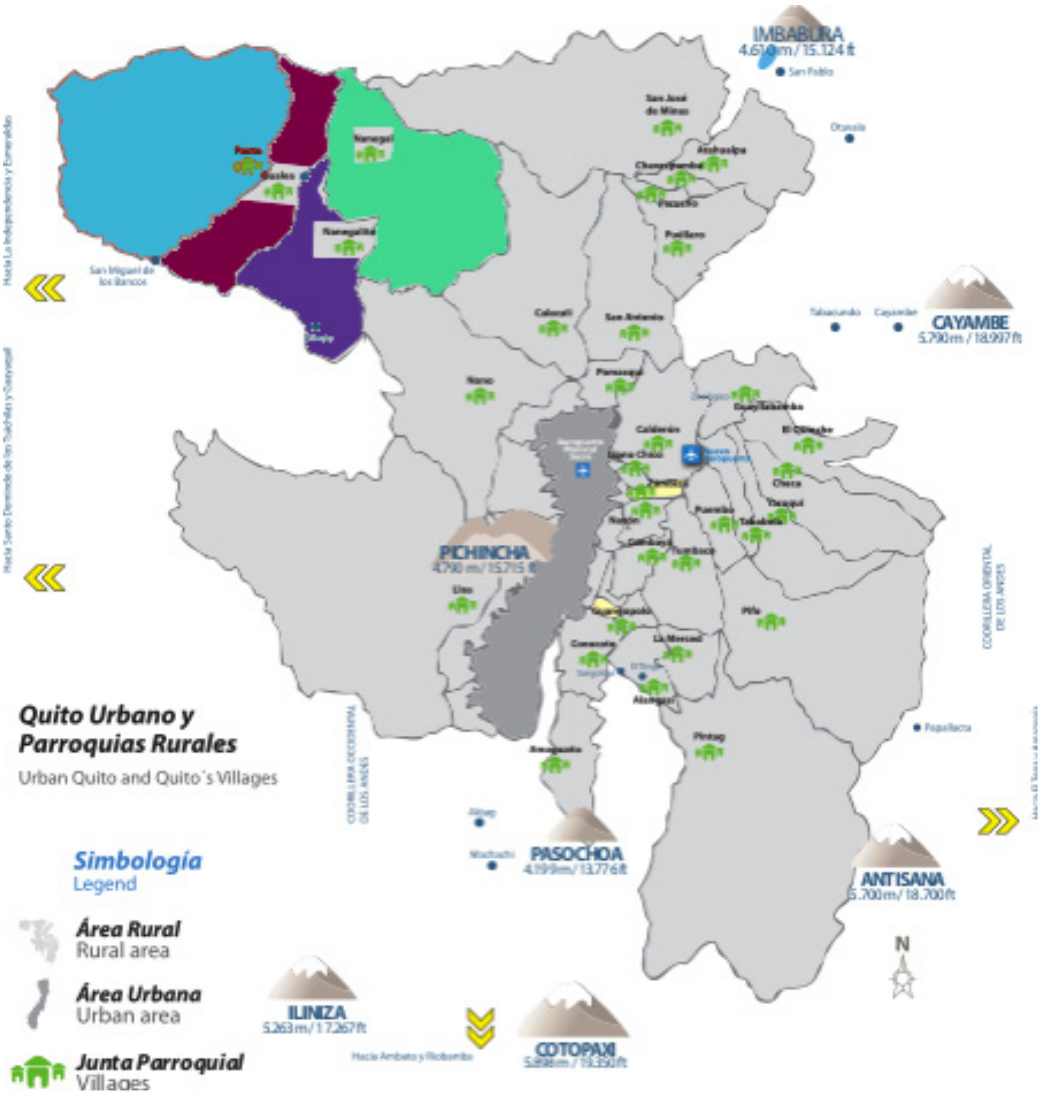
The climate change projection analysis presented in this report was conducted as a subcomponent of a larger, baseline investigation into the climate and non-climate risk factors influencing disease transmission and vector-presence risk in four rural parishes in northwest Quito County (Canton). Through its Quito Climate Change Strategy (QCCS), the Metropolitan District of Quito (MDQ) has begun a climate resilience planning process focusing on the dual need of mitigation and adaptation. Health, ecosystems and biodiversity, and climate impacts on these are some of the strategic sectors identified as priorities in the QCCS. However, lack of data and systematic research on the interdependencies between these sectors is making it difficult to develop and assess short-term (next 5 years) and longer-term strategies for dealing with vector-borne diseases (VBD). The purpose of this project is to provide policy-relevant data on Chagas disease, leishmaniasis, malaria, chikungunia and dengue fever and relevant socioeconomic, climatic and land-use change factors influencing disease rates and transmission in four rural parishes (*parroquias*): Nanegal, Nanegalito, Pacto and Gualea (NNPG) in the northwest of the Quito Canton—see Figure 1.

This current study must be considered a baseline vector-climate risk investigation to lay the foundation for further, continued monitoring and evaluation of the situation in the communities and for enhancing the process-based overall climate risk planning and

adaptation efforts underway in Quito. Lack of observational data—historical climate, vector presence and disease serology, and socioeconomic patterns—is the major factor limiting a more comprehensive investigation of potential shifts in vector-climate risks for these rural parishes. Nonetheless, study findings can provide important baseline information for developing further health risk monitoring and evaluation programs, improving health access, and increasing public awareness about the links between vector-borne disease, climate change, human behavior in the home and in the fields, and land-use conversion.

FIGURE 1

Four-parish study area in northwest Quito Canton for the vector-risk and climate change analysis. Source for base map: Dr. Renato Leon 2015.



2. Methodology

Data is the primary limiting factor determining the type of suitable climate change analysis, at what scale, and the results. Drawing a causal relationship between climate variables and vector range and life cycle is difficult without sufficient observational data—either of the vectors or of climate variables. The methodology section describes the data compilation and gridding, and downscaling techniques adopted that were appropriate for such data limitations as encountered in this study. The techniques draw on methods established in other vector-climate risk (Moore et al. 2012; Lowe et al. 2015) or climate change (Bajat et al. 2012; Opitz-Stapleton and Gangopadhyay 2011) studies in data-limited environments with diverse terrain, such as Uganda or Nepal. It also documents why the spatial scale for gridding the data could not be of higher resolution and the caution that should be exercised when using the multitude of climate data sets that are now available online.

2.1 Data Compilation & Gridding

High-resolution, gridded climate information is desirable in many kinds of climate risk and impacts studies, from water resources management to ecological and health assessments. Gridded climate data are produced by smoothing weather station data (points) over a geographical area using an interpolation technique (Haylock et al. 2008; Bajat et al. 2012). Ideally, such investigations would be able to access gridded climate information that reliably captures local conditions at a spatial resolution of 1 km (for some types of health studies) to 50 km (river basin-scale or agricultural studies) for a minimum of 30 to 40 years of observation. In many countries, however, weather stations have been installed in remote locations only since the 1990s and the overall spatial density of stations in hilly and mountainous terrain—where there can be significant variations in microclimates—continues to remain low at distances of 100 km or more between stations. Some terrain climate-forcing factors are described in Table 1.

TABLE 1

Terrain or water features known to influence spatial-climate relationships (Daly 2006: 709).

Factor	Assessment question	Precipitation	Summer maximum temperature	Summer minimum and winter maximum and minimum temperature
Elevation	Are there valleys, hills or mountains present?	Complex patterns; mainly local increase with elevation, except above maritime layer or tradewind inversion	Strong, predictable decrease with elevation, except maritime inversions	General decrease with elevation, but complicated or even reversed by inversions and cold air drainage
Terrain-induced climate transitions	Is there evidence of sharply-defined climate regimes defined by terrain features?	Rain shadows—precipitation maxima on windward slopes, sharply transitioning to minima on leeward slopes	Blockage of marine airflow penetration, producing sharp contrast between coastal and inland temperatures	Divides air masses, such as continental and maritime
Cold air drainage	Are there valleys, hills or mountains present?	Limited effects	Limited effects	Temperature inversions in protected valleys, even in tropics; very extensive at higher latitudes
Coastal zones	Are there oceans or large lakes present?	Wetter coastal areas, if water body is significant source of moisture	If water-land temps differ, large gradients between coastal and inland temperatures	If water-land temps differ, large gradients between coastal and inland temperatures

Ecuador has a diverse terrain, from ~2,300 km of coastline to las sierras with snow-capped volcanoes like Mount Pichincha (~4,698 m). Proximity to the coasts, elevation and the complex orography strongly influence Ecuador's local climate transitions, particularly rainfall patterns and temperature at scales of ~10 km or less. A high station density of at least 10 km, or a dynamic climate model that simulates high-resolution climates and compares well with observations, is necessary to produce high-resolution gridded climate data. At scales of approximately 50 km, the factors in Table 1 have moderate influence on a single grid's climate.

2.1.1 Climate Variable Selection

The climate change variables selected for study and downscaling were determined: 1) in collaboration with the vector risk modelling team; 2) based on a literature review of vector range-climate references; and 3) the likelihood of variables being recorded and reported in weather station data. Variables such as humidity, sunshine hours and solar radiation are often not collected and/or reported in weather station data. The vector risk modelling team initially constructed and calibrated their macro-scale vector model using BioClim climate variables (Hijmans et al. 2005). The standard variables used in ecological niche modelling include minimum, maximum and mean temperature, and precipitation, at quarterly (3-month) and annual time steps. As the limited extent of historical vector observation data became apparent, it was determined that the vector-climate relationships could only be calculated on an annual and seasonal basis (rainy and dry—see Section 3 for a discussion of season determination). Based on the data needs of the vector team, the final climate variables were selected for study and downscaling over the following time epochs (Table 2):

TABLE 2

Climate variables and future time epochs for climate change downscaling analysis

Climate Variable	Time Epoch
Precipitation	Historical: 1976 – 2005
Minimum temperature	Near-term, the 2020s: 2010 – 2039
Maximum temperature	Mid-term, the 2050s: 2040 – 2069
Mean temperature (calculated variable)	Long-term, the 2070s: 2060 – 2089

2.1.2 Data situation in the four-parish study area and surrounding region

The long-term operations and data collection from weather stations in Ecuador are managed by a number of institutions, the principal being the Instituto Nacional de Meteorología e Hidrología (INAMHI), the Instituto Oceanográfico de la Armada de Ecuador (INOCAR) and the Fuerza Aérea Ecuatoriana (FAE). FAE stations are located at airports and air bases. The agencies collate and report data to a variety of international databases, namely the World Meteorological Organization (WMO) or the Global Historical Climatology Network (GHCN), which are two of the primary international climate data repositories.

INAMHI has been publicly releasing monthly station data in Anuarios Meteorológicos since 1990. Not every station is consistently reported in every Anuario, leaving significant data gaps. Furthermore, none of the agencies consistently reports data to the WMO or GCHN.

The parishes are marked by diverse, hilly, forested terrain in which vegetation is being cleared for agriculture; geography and land use change create different microclimates in and around the communities. The large-scale, approximate climates of the four study parishes are represented by a single weather station at Nanegalito (M339), at least as is publicly available. Data at M339 have been collected and/or reported only intermittently since 1991. The next closest station at Inaquito (M327) is 22 km away, situated nearly 1200 m higher and has been relocated at least once between 1970-2010. The low weather station density is not capable of capturing the microclimate conditions that strongly influence local vector habitats.

Other stations that we drew on for our analysis have moved one or more times during the reporting period, which influences continuity and may introduce artificial trends in climate variables[1]. For instance, the station at Inaquito (M024) is reported as being located at one elevation (2812 m) in earlier records, but in the 2010 Anuario (INAMHI 2010), it is located at 2789 m. Other stations publicly report data only for a small portion of the time they are documented as being in operation; many also have significant gaps in the records. Chiriboga (M116 – 30 km from M339) was established in the 1960s according to Anuarios but does not have publicly available data before 1990. No station metadata—documents describing the instrumentation or changes in measurement protocol or station location—is available for any of the stations. This further complicates efforts for validating and conducting quality controls across the data sets.

A growing number of climate scientists are strongly cautioning about the growing availability of very high-resolution (less than 10 km) gridded climate data sets in which users may "equate resolution with realism … regions having significant terrain features, and also significant coastal effects, rain shadows, or cold air drainage and inversions are best handled by sophisticated systems that are configured and evaluated by experienced climatologists" (Daly 2006: 707). Ecuador remains one of those countries where strong caution must be exercised when using internet-based, very-high resolution gridded climate data sets (e.g., WorldClim or CliMond[2]) that have not been verified and quality-controlled against available observation data in all countries.

While INAMHI, INOCAR and FAE have been expanding station coverage since the 1990s, historically low station density prior to then, interruptions in data collection, and lack of long-term observations make it difficult to spatially interpolate historical climate trends and statistics at scales smaller than 50 km. *Given the low station density and short observation records in the study location, the study team decided that the highest resolution a climate data set could be gridded to was ~50 km for the purpose of this study.*

2.1.3 Historical Data Collection

The domain for analysis was set as [-79.75 to -78.25W: -1.25 to 1.25N], with a grid spacing of 0.5° x 0.5° or approximately 50 km by 50 km. Given the incomplete nature of most of the data sets, reported observations for a sub-daily to monthly time scale were gathered for stations in the domain from a variety of sources (Table 3).

Photo above: Simon Matzinger 2014. Reproduced under CCBY2.0 License

A quasi-complete record for each station over the period of 1970-2010 could only be compiled using multiple sources; no stations presented with complete records over the whole period from a single source. Many station records only report precipitation data, or short records for temperature. All of the reported stations were missing data for some years, with most averaging a 5% to 10% gap in the record. Such data gaps are significant for stations with short records and make it difficult to conduct trend analysis and other tests.

Station data were requested for these stations and others within the study domain from INAMHI in March 2015. However, due to delays, INAHMI could not supply the data before late fall 2015. Given project time constraints—namely the time required for conducting the climate downscaling and then constructing the vector-climate risk models, each which required several months of work—it was necessary to compile station data from sources other than INAMHI.

Monthly datasets were compiled from the partial sub-daily, daily and monthly records from the various sources for each station over the approximate period of 1970-2010. Given data gaps and variances between reported values for the same station by different sources, data are considered *partially* valid only from 1975 or 1980 onward, depending on the station. This implies that the data quality for many of the stations cannot be verified and all trend analysis of individual stations must be interpreted with caution.

TABLE 3

Historical Station Data and Sources

Stations Considered for Study Domain			
Station Name & ID	Station 2010 Coordinates (Decimal Degree)	Reported Climate Variables	Period of Record/ Data Gaps or issues
Chiriboga (M116)	78.76W, -0.2N, 1750m	precip only	1990-2010/ yes
Chontal Bajo (M327)	78.44W, 0.14N, 675m	precip only	1990-2010/ yes
Canar* (M031)	78.93W, -2.55N, 3120m	precip, tmax, tmin, tmean	pcp & tmean 1970-2010/ yes tmax, tmin 1990-2010/ yes
La Concordia (M025)	79.36W, 1.6N, 379m	precip, tmax, tmin	pcp 1970-2010/ yes tmax, tmin 1990-2010/ no
Esmeraldas (M058)	79.61W, 0.97N, 7m	precip, tmax, tmin	pcp, tmax, tmin 1970-2010/ yes
Guayaquil* (M075)	79.61W, -2.25N, 6m	precip, tmax, tmin	pcp, tmax, tmin 1970-2010/ yes
Inaquito (M024)	78.48W, -0.17N, 2812m	precip, tmax, tmin	pcp 1981-2010/ yes tmax, tmin 1990-2010/ yes
Inguicho (M001)	78.4W, 0.25N, 3185m	precip, tmax, tmin	1990-2010/ yes
Izobamba (M003)	78.55W, -0.35N, 3058m	precip, tmax, tmin	pcp 1970-2010/ yes tmax, tmin 1990-2010/ yes
Manta (M074)	80.73W, 0.93N, 15m	precip, tmax, tmin	pcp unreliable tmax, tmin 1978-2010/ yes
Mariscal Sucre (M055)	78.8W, -0.22N, 2400m	precip, tmax, tmin	pcp 1978-2000/ yes tmax, tmin 1978-2010/ yes
Nanegalito (M339)	78.58W, 0.00N, 1580m	precip only	1991-2010/ yes
Pasto Narin (USAF 80342)	77.45W, 1.7N, 1826m	precip, tmax, tmin	pcp 1970-2000/ yes tmax, tmin 1978-1999/ yes
Pichilingue (M006)	79.76W, -1.17N, 73m	precip, tmax, tmin	pcp & tmean 1970-2010/ yes tmax, tmin 1990-2010/ yes
Puerto Ila (M026)	79.35W, -0.48N, 260m	precip, tmax, tmin	pcp & tmean 1970-2010/ yes tmax, tmin 1990-2010/ yes
Puerto Viejo (M274 and M005) – records unclear	80.45W, -1.03N, 44m	precip, tmax, tmin	pcp & tmean 1970-2010/ yes tmax, tmin 1975-2010/ yes
Santo Domingo (M027)	79.33W, -0.38N, 554m	precip only	1970-1998/ yes
San Juan (M124)	79.32W, -0.95N, 223m	precip, tmax, tmin	pcp & tmean 1970-2010/ yes tmax, tmin 1990-2010/ yes

Station Data Sources – used to compile dataset for each station
World Weather Records from the World Meteorological Organization (Dattore personal communication)
Global Historical Climatology Network – Monthly and Daily (Peterson et al. 1998; Menne et al. 2012)
Integrated Surface Database Hourly (Lott et al. 2001)
Tutiempo.Net – reports FAE and INOCAR stations
INAMHI Anuarios (INAMHI)
Dr. Mercy Borbor (personal communication)

Notes:

1) * indicates station not used in final gridded dataset as considered too distant from the study domain and/or due to significant data issues.

2) Most stations have discontinuities indicating possible station relocation one or more times during record

The final station data sets used to adjust a gridded climate data set cannot be completely verified for quality or homogeneity, despite undergoing standard meteorological variable checks. Artificial trends or discontinuities might exist, and influence analysis to detect potential climate change shifts or trends in the historical data.

2.1.4 Gridding of Historical Data

The low spatial station density, coupled with gaps and quality issues, led us to use the station data as anchors for adjusting an existing high-resolution gridded dataset, the Climate Research Unit (CRU) TS3.22. The CRU TS3.22 dataset contains monthly data for surface climate variables that are interpolated to a 0.5° x 0.5° latitude/longitude using homogenized station data reported by country meteorological agencies to the World Meteorological Organization or the U.S. National Climate Data Center[3] (Harris et al. 2013). Stations used to generate the gridded climate data undergo strict quality control measures and methods are used to correct for anomalies or reject spurious data. For the study domain, the CRU TS3.22 gridded data consists of 24 grids.

The resolution of the CRU dataset is still partially influenced by local weather patterns and topography, though not as much as if it had been gridded to a resolution of less than 10 km. While temperature variation is most dependent on elevation, precipitation varies significantly with orography that would not be completely captured by the stations used in CRU TS3.22 for the Ecuadorian domain. We decided to calibrate the CRU data with the compiled station data and Tropical Rainfall Measurement Mission - Multi-satellite Precipitation Analysis (TRMM-TMPA 3B43, Huffman et al. 2007). Recalibrated gridded ensemble historical climate datasets were generated

by an un-weighted averaging of compiled station data with the gridded datasets; lack of time prevented testing of various regression models for different weighting schemes (Moore et al. 2012).

1. Stations were matched to the closest CRU TS3.22 grid through great circle distancing using 'Fields' in R Project (Nychka et al. 2016).
2. The TRMM 3B43 data were matched to the closest CRU TS3.22 grid through great circle distancing using Fields in R Project (Nychka et al. 2016).
3. An unweighted ensemble average of the sources for that grid was conducted to recalibrate the grid's climate variables.

The final grid spacing and coordinates of the grids was determined by the underlying CRU TS3.22 gridded climate dataset (Table 4).

TABLE 4

Grid coordinates for the gridded observation climate datasets

Grids	Longitude	Latitude
G1	79.75 W	-1.25 N
G2	79.25 W	-1.25 N
G3	78.75 W	-1.25 N
G4	78.25 W	-1.25 N
G5	79.75 W	-0.75 N
G6	79.25 W	-0.75 N
G7	78.75 W	-0.75 N
G8	78.25 W	-0.75 N
G9	79.75 W	-0.25 N
G10	79.25 W	-0.25 N
G11	78.75 W	-0.25 N
G12	78.25 W	-0.25 N
G13	79.75 W	0.25 N
G14	79.25 W	0.25 N
G15	78.75 W	0.25 N
G16	78.25 W	0.25 N
G17	79.75 W	0.75 N
G18	79.25 W	0.75 N
G19	78.75 W	0.75 N
G20	78.25 W	0.75 N
G21	79.75 W	1.25 N
G22	79.25 W	1.25 N
G23	78.75 W	1.25 N
G24	78.25 W	1.25 N

2.1.5 CMIP5 Climate Model Selection

The Coupled Model Intercomparison Project Phase 5 (CMIP5) represents the current suite of general circulation models (GCMs) used to evaluate potential climate change and inform the numerous studies that comprised the Intergovernmental Panel on Climate Change's Fifth Assessment Report (IPCC AR5). GCMs project how the climate might change, given scenarios of human-controlled factors like greenhouse gas concentrations and land-use, which are accounted for as representative concentration pathways (RCPs) in the CMIP5. There are four different RCP scenarios used in GCMs to simulate possible ranges of change given different concentrations of greenhouse gases in the atmosphere. The four are RPC 2.6, RCP 4.5, RCP 6 and RCP 8.5. RCP 4.5 is a moderate scenario and assumes that emissions peak around 2040 and then decline, whereas RCP 8.5 is a high scenario assuming emissions continue to rise (van Vuuren et al. 2011). The CMIP5 models project changes in future climate variables such as precipitation, temperature and humidity over broad spatial scales of ~100 to 250 km.

No single climate model will ever be able to project the *exact* changes in rainfall, temperature, or other climate variables in any given year or period in the future for any part of the world. This is because no one knows exactly what emissions, populations, and land-use changes might occur in the future, and due to the limitations and assumptions of the models themselves (Collins et al. 2013). Using the projections from a single model is not scientifically rigorous and can lead to an underestimation of climate risks. It is necessary to use projections from multiple GCMs, each driven by one or more RCPs, to capture a possible range and trend of changes for a region of the world.

This study downscaled projected climate variables from seven CMIP5 models, each running two RCPs—RCP 4.5 and RCP 8.5—in order to capture the plausible range of change for Ecuador (Table 5). However, the CMIP5 data portal has been undergoing a reconfiguration and data migration since early 2015. Not all seven GCMs were available for the entire future period (2005-2100) for which we wished to downscale and project potential changes for the domain. We used the total number of available models out of the seven for each of the three future time periods, with the number used decreasing the farther into the future.

TABLE 5

CMIP5 Climate Models Used in Downscaling

Model	Modelling Center	Grid Resolution at equator (long x lat)
Bcc CSM1.1M	Beijing Climate Center, China Meteorological Administration	~310 km x 310 km
CanESM2	Canadian Centre for Climate Modelling & Analysis	~312 km x 310 km
Csiro MK3.6.0	Commonwealth Scientific & Industrial Research Organisation (CSIRO)/ Queensland Climate Change Centre of Excellence	~312 km x 307 km
HadGEM2-ES	UK Met Office Hadley Centre	~208 km x 139 km
Miroc ESM	Japan Agency for Marine-Earth Science & Technology, Atmosphere & Ocean Research Institute (University of Tokyo), and National Institute for Environmental Studies	~312 km x 310 km
Mpi ESM-MR	Max Planck Institute for Meteorology	~210 km x 206 km
Ncar CSSM4	National Center for Atmospheric Research (NCAR, USA)	~139 km x 105 km

Description

1. Simulated daily precipitation, and 2-meter minimum and maximum temperature for two time periods:

    - Historical: 1970 – 2005

    - Future: 2005 – 2100. Only two models with data through 2100 were available on the Program for Climate Model Diagnosis and Intercomparison (PCMDI) data portal. See Section 3.2 for a discussion of the final model sets that were used in downscaling for each of the three future time periods.

2. Data downloaded from CMIP5 Multi-Model Ensemble Dataset: http://pcmdi9.llnl.gov/esgf-web-fe/. The PCMDI data portal underwent a reconfiguration during 2015, and not all of the datasets from the desired models were available. The data portal has now transitioned to https://pcmdi.llnl.gov/projects/esgf-llnl/ (Feb 2016), but is still undergoing work at time of this study's publication and not all datasets are available.

3. Additional CMIP5 datasets provided by Dr. Caspar Amman at NCAR.

2.2 Bias Correction and Climate Change Downscaling

GCMs model the interactions between the land, ocean and atmosphere that influence climate, but they do so on a large-scale, typically between ~150 to ~300 km. As a result, they cannot fully capture local climate processes, will over- or under-represent variables like temperature or precipitation and not accurately reproduce local variability. As a result, it is necessary to downscale—find a relationship between the large-scale

climate model values and the local observation values—and correct for the biases (too hot, too cold, etc.) in the model values.

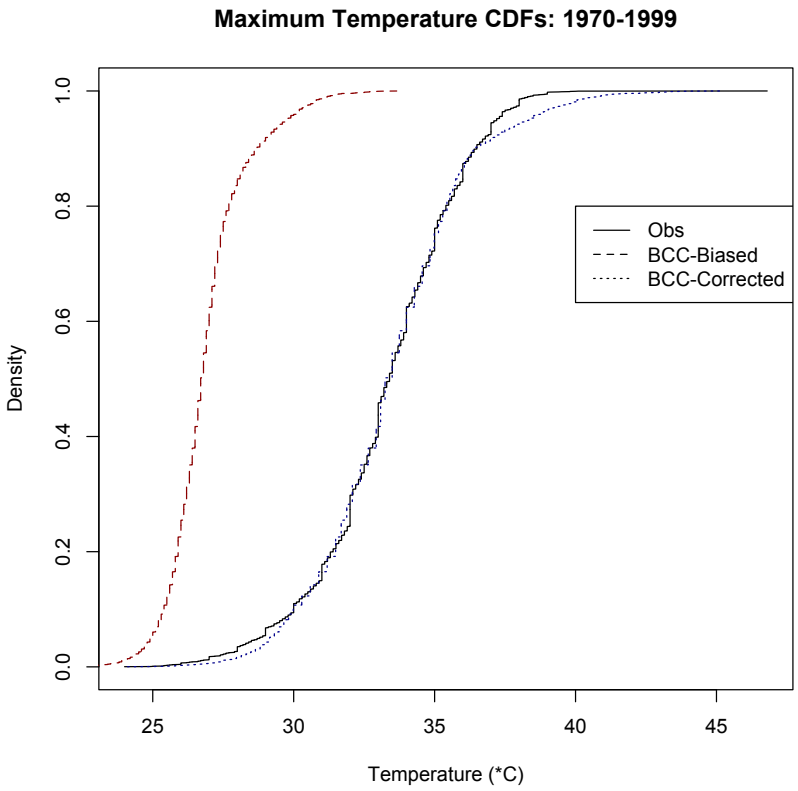
There are many methods for downscaling and bias correcting GCM output; these methods fall into either a dynamical or statistical downscaling category (Opitz-Stapleton and Gangopadhyay 2011; von Storch et al. 2000; Wilby et al. 2004). The selection of downscaling method is determined by a number of factors, including:

1. Observational data quality
2. Computational and time resources
3. Ability to establish and verify types of relationships between large-scale climate variables and local climate conditions

We employed a quantile-quantile mapping technique to statistically downscale the four climate variables (refer to Table 2) and correct for model bias without losing the important climate change signals embedded in the model projections. Quantile-quantile mapping is well-suited to data-poor, time-limited situations such as those encountered in this study.

FIGURE 2

Quantile mapping plot showing a biased model (red) and downscaled model (dots) in comparison with the observed (solid black).



The quantile mapping method has been used in a number of climate change studies, typically to downscale temperature and precipitation (Quintana- Seguí et al. 2011; Hashimo et al. 2007; Gudmundsson et al. 2012). The method involves developing a transfer function from the cumulative distribution function (CDF) of the model simulations to match the CDF of the observation data (Figure 2). In order to account for the possibility that climate change will alter the variability and the skew of the distribution over time, in addition to the mean, we used the equidistant mapping method proposed by (Li et al. 2010b). This method allows for the possibility of non-stationarity in the observational data, which is necessary given the trends (see Section 3.1) that were seen in the historical gridded climate dataset.

$$x_{m,adj} = x_{m,fut} + F_{obs}^{-1}\left(F_{m,future}\left(x_{m,fut}\right)\right) - F_{m,past}^{-1}\left(F_{m,fut}\left(x_{m,fut}\right)\right)$$

x_m = the model variable, *adj* is the downscaled value, *obs* is the observational training data, *past* is the historical replication model variable, and *fut* is the uncorrected model variable

F = a transfer function derived either from the observation data or from the model data

We downscaled each variable—precipitation, tmin and tmax—separately for three time steps (annul, rainy season and dry season) as described in Li et al., coded in R (v.3.1.1 'Sock it to Me') and drawing from the 'qmap' package (Gudmundsson et al. 2012).

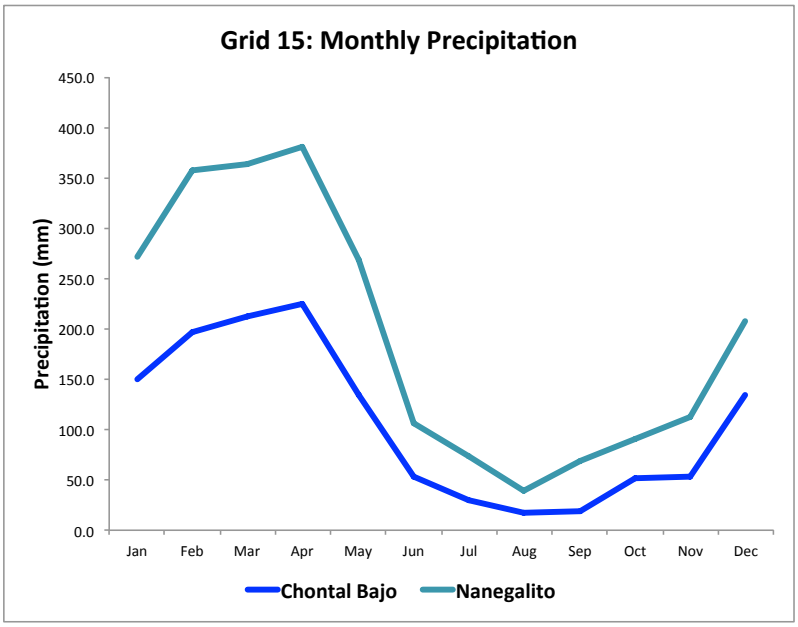
The downscaling and projection is done separately for each model or over the median ensemble member from the suite of models in order to capture a broader potential range of climate change for the domain. Selection of which set of models to downscale is determined by analyzing each model's skill at replicating historically observed climate statistics. The skill score analysis and discussion of which models were ultimately downscaled is contained in Section 3.2.

3. Results

Ecuador's climate is broadly characterised by two seasons—the rainy season and the dry season. The study team analyzed the monthly gridded climate data, particularly for Grid 15 that encompasses the four-parish area, to determine the lengths of the rainy and dry season. As can be seen in Figure 3, the rainy season duration is approximately from December through May; the dry season is roughly from June through November.

FIGURE 3

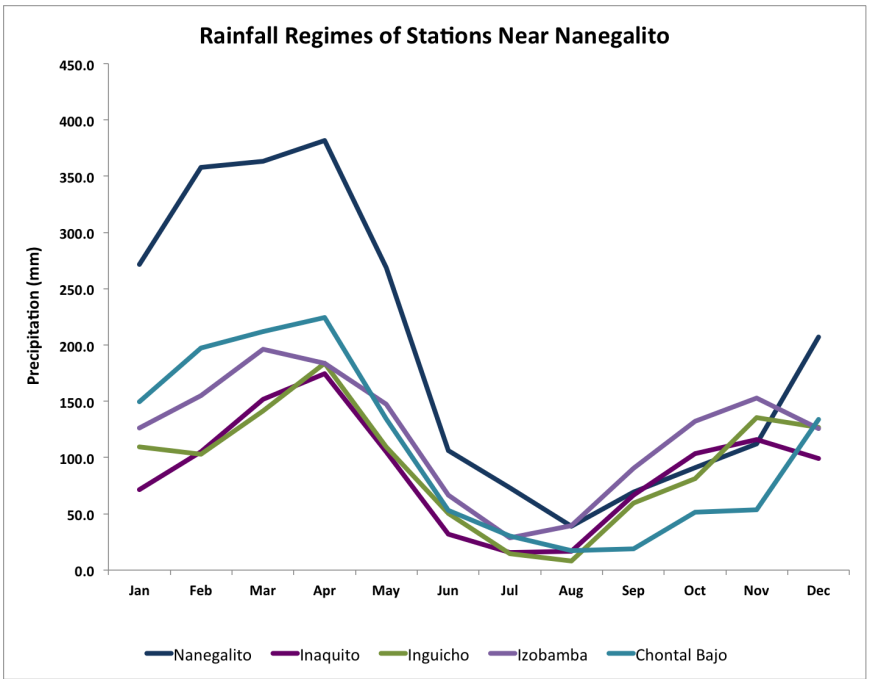
Rainfall regime of the two stations (Chontal Bajo and Nanegalito) located in Grid 15



There are differences in the onset and withdrawal of the rainy season, and overall rainfall regimes over very short distances from Nanegalito due to the combined effects of local orography and topography with large-scale climate processes (discussed below, see also Celleri et al. 2007). Stations at higher elevations (e.g., Inaquito – 2812 m, Inguicho – 3185 m and Izobamba – 3058 m) display bimodal rainy seasons, even though they are only 22 km, 34 km and 39 km, respectively, away from the station at Nanegalito (Figure 4). This high degree in spatial and temporal variability, coupled with poor station data, presented a challenge when gridding the dataset and deciding how to demarcate the seasons for the downscaling and vector-risk analysis. Given that the focus of the overall study is on the four-parish study area centered around Nanegalito, for gridding purposes, we adopted the single rainy season/dry season regime of Nanegalito.

FIGURE 4

Rainfall regimes of all stations within a 40 km radius of Nanegalito. The length and quality of the record is different for each station, impacting the stability of the monthly median rainfall statistic..

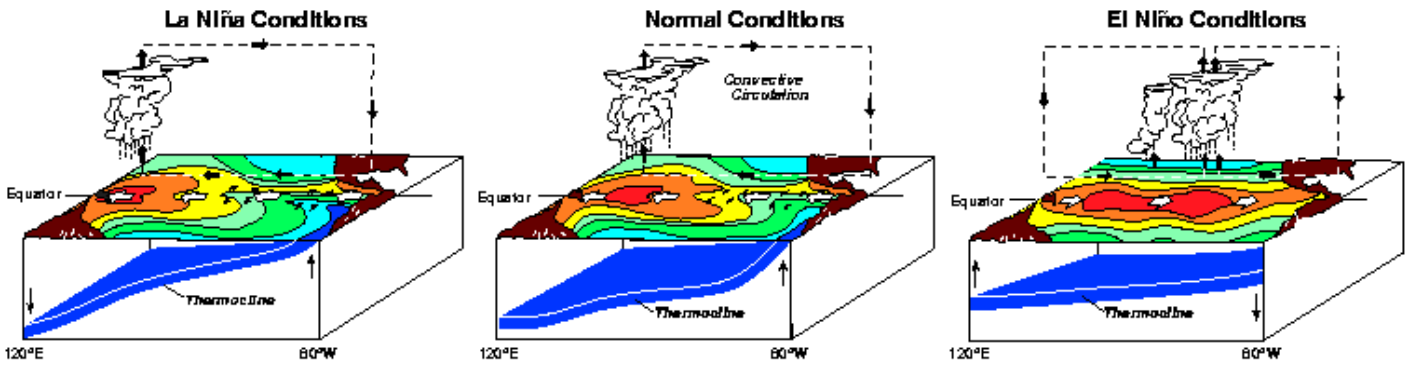


There is considerable variability in Ecuador's precipitation within a year (seasonality), year-to-year and on a multi-decadal basis. Rainy season onset and withdrawal is largely determined by the movement of the Intertropical Convergence Zone (ITCZ). The ITCZ marks the zone of convergence of the northeast and southeast trade winds as an area of semi-permanent low-pressure that leads to enhanced convection and rainfall. It generally oscillates around ~20° north and south of the equator, although the ITCZ can extend as far north as 40° over the western north Pacific. The location of the zone is largely determined by the sun's zenith and it is almost always located in whichever hemisphere is currently experiencing summer.

Inter-annual and multi-decadal variability is strongly influenced by large-scale climate processes like the El Niño Southern Oscillation (ENSO) and the Pacific Decadal Oscillation (PDO) (Pineda et al. 2013; Bendix and Bendix 2006; Artaega et al. 2006). ENSO and PDO are natural variations in the earth's climate that happen on cyclical bases, with an ENSO cycle lasting 2 to 7 years and PDO roughly every 20 to 30 years. The sea surface temperatures of the Pacific Ocean are normally warmer in the west (near Australia) and cooler along the South American coast. During ENSO (Figure 5), the location of the warm water moves and this influences large-scale atmospheric circulation and rainfall patterns.

FIGURE 5

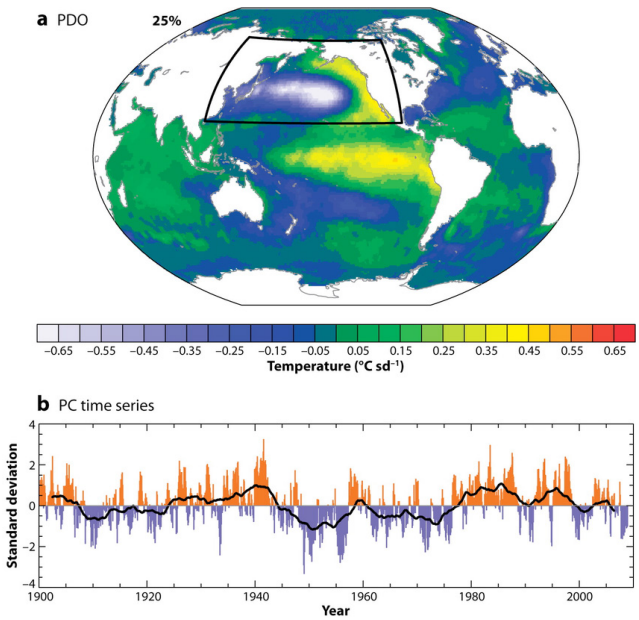
El Niño Southern Oscillation (NOAA/PMEL/TAO 2016).



The PDO (Figure 6) is detected as either abnormally warm or cold sea surface temperatures in the Pacific Ocean near the tropics and north of 20°N; it influences precipitation and temperatures along North and South America and Pacific hurricane activity (Mantua &Hare 2002; Deser et al. 2010). PDO can magnify or diminish the impacts of ENSO depending on whether they are in the same or opposite phase, with a positive PDO plus strong El Niño leading to particularly heavy rainfall in equatorial coastal South America (Wang et al. 2014).

FIGURE 6

Pacific Decadal Oscillation warm phase (Deser et al. 2010)



Deser C, et al. 2010.
Annu. Rev. Mar. Sci. 2:115–43

Given its proximity to the equator, temperatures do not vary much with the seasons. Instead, temperatures at a given location within Ecuador are more determined by distance to the coasts and by elevation. Higher elevations, and valley areas within the mountains, are much cooler than coastal regions.

3.1 Historical Trends

A two-sided non-parmetric Mann Kendall trend analysis test was conducted for the stations (Nanegalito M339 and Izobamba M003) in the four-parish study area and for the grid (Grid 15) representing them in the gridded climate dataset. It is ideal to use a non-parametric trend test to account for the possibility of non-linear trends, with significant outliers, over the length of a station's record. Trends with a Mann Kendall rho value that was not statistically significant at the 95th percentile for the length of available record were rejected as not being true trends.

The following significant trends in precipitation and minimum temperature are seen in the four-parish study area (Table 6):

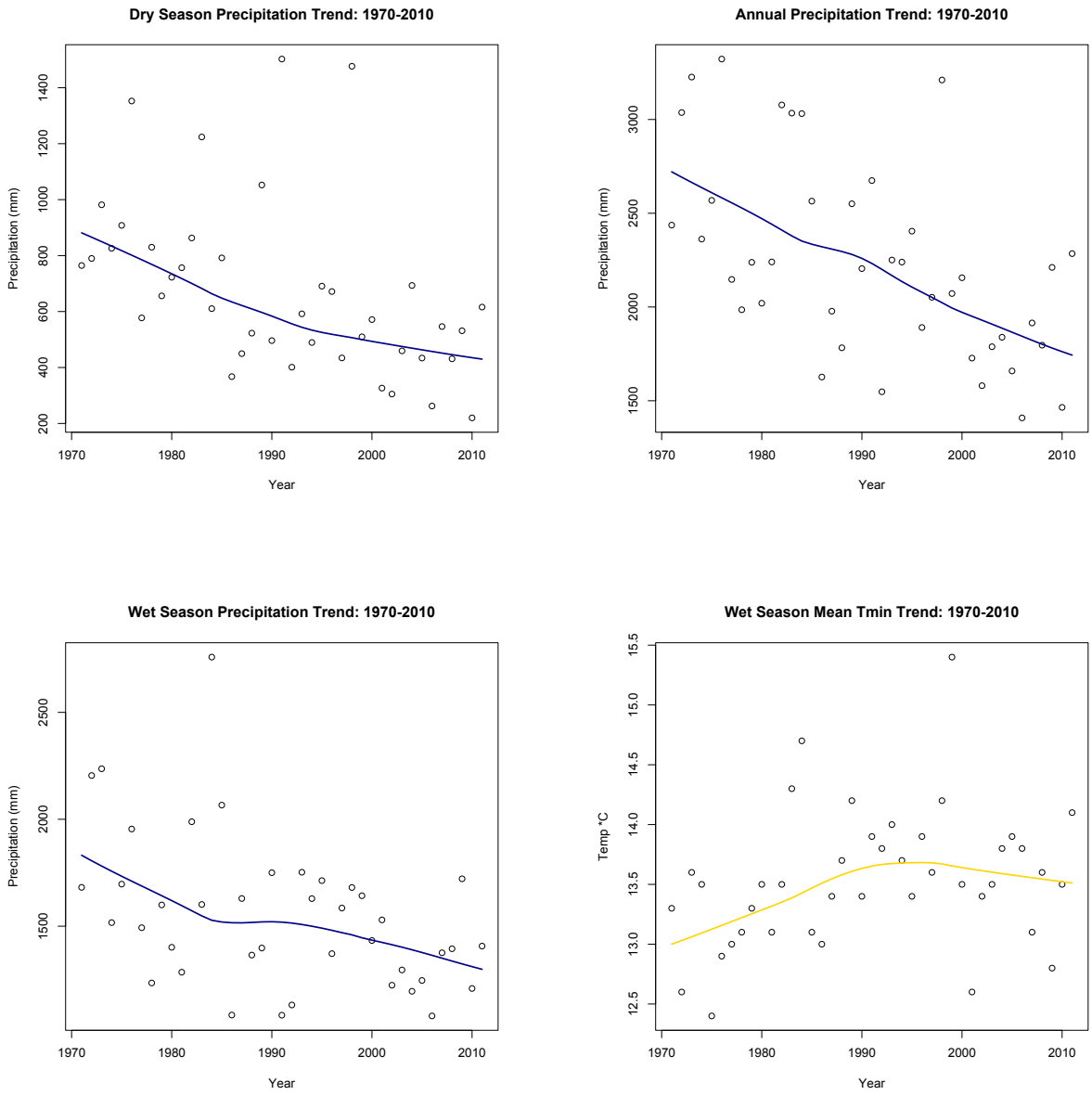
TABLE 6

Statistically significant historical climate trends in four parish area

Annual	Rainy Season (Dec – May)	Dry Season (June – Nov)
IZOBAMBA (M003)		
Minimum Temperature Trends: 1990-2010		
0.5°/ decade +	0.5°/ decade +	0.4°/ decade +
GRID 15: 78.5W to 79W, 0N to 0.5N. Centered at 78.75W, 0.25N		
Minimum Temperature Trends: 1970-2010		
no trend	0.1°/ decade +	no trend
Precipitation Trends: 1970-2010		
-238 mm/decade	-121 mm/decade	-116 mm/decade

FIGURE 7

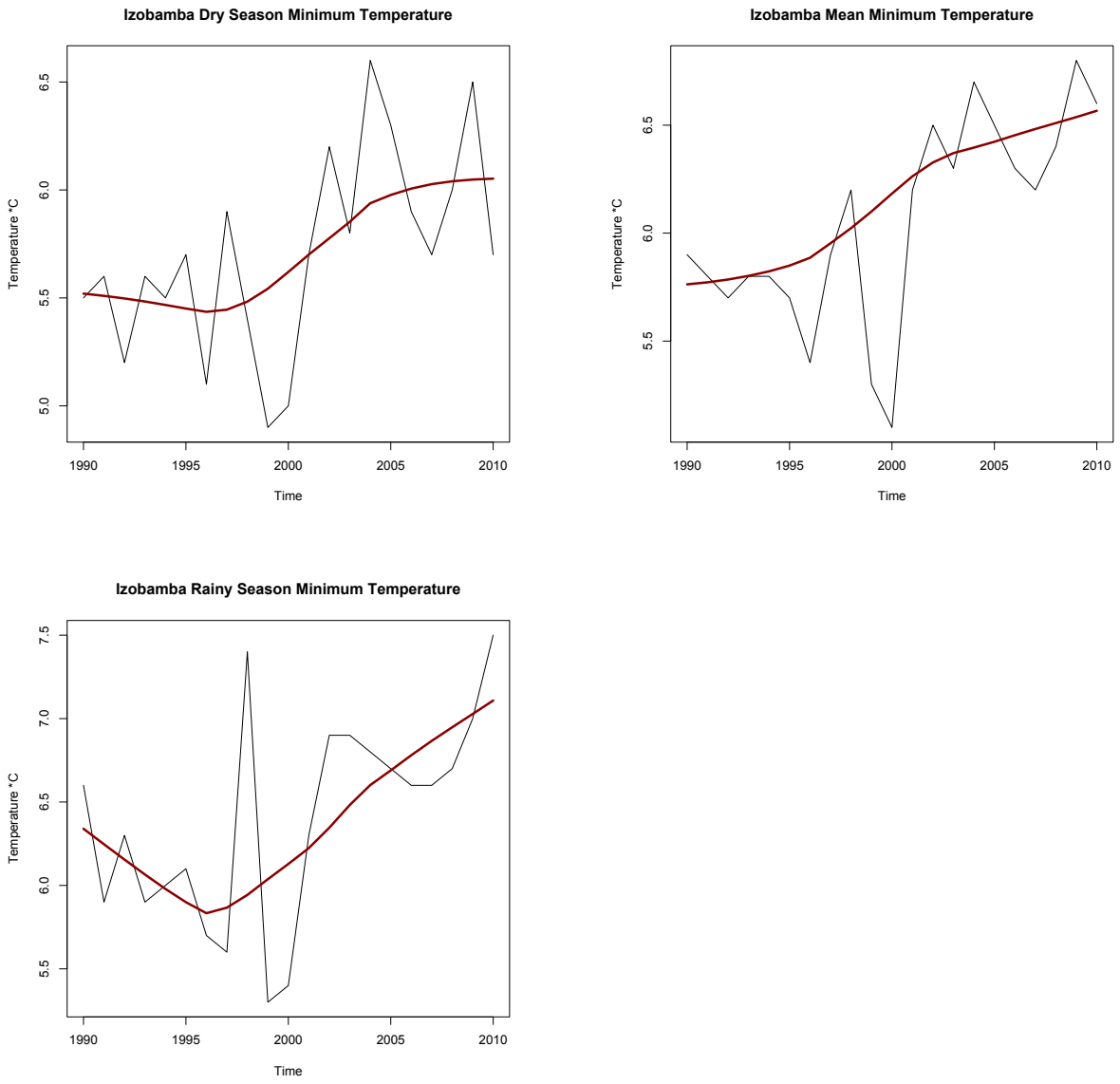
Historical climate trends in Grid 15, encompassing four-parish area, for 1970-2010



No other statistically significant trends than those in Table 6, Figure 7 and Figure 8 are seen in temperature (mean and maximum) on an annual or seasonal basis in the study area. The differences in trends at the various stations—with Izobamba clearly demonstrating increasing minimum temperatures and Nanegalito showing only weak decreasing precipitation trends—further points to the high spatial variation in micro-climates over short distances and the need for a higher density of stations.

FIGURE 8

Izobamba significant climate trends over 1990-2010



Potential decreases in Nanegalito's annual and season precipitation may be developing (Table 7 and Figure 9). The reasons why we cannot yet declare the trends to be relevant are as follows:

1. The trends are only statistically significant at the 90th percentile.
2. There is also a sharp discontinuity in Nanegalito's precipitation data in 2003, with half of the year missing in the Anuario (INAMHI 2003)—see Figure 9.
3. Only a short period of record is available for Nanegalito's precipitation data—1991-2010—with significant data gaps in 1991, 1992, 1994 and 2003.

We advise continued monitoring of station data in Nanegalito to establish whether the trend is significant. Given that significant decreasing precipitation trends *are* observed for Grid 15 as a whole, it is plausible that the decreasing trends observed at Nanegalito are relevant.

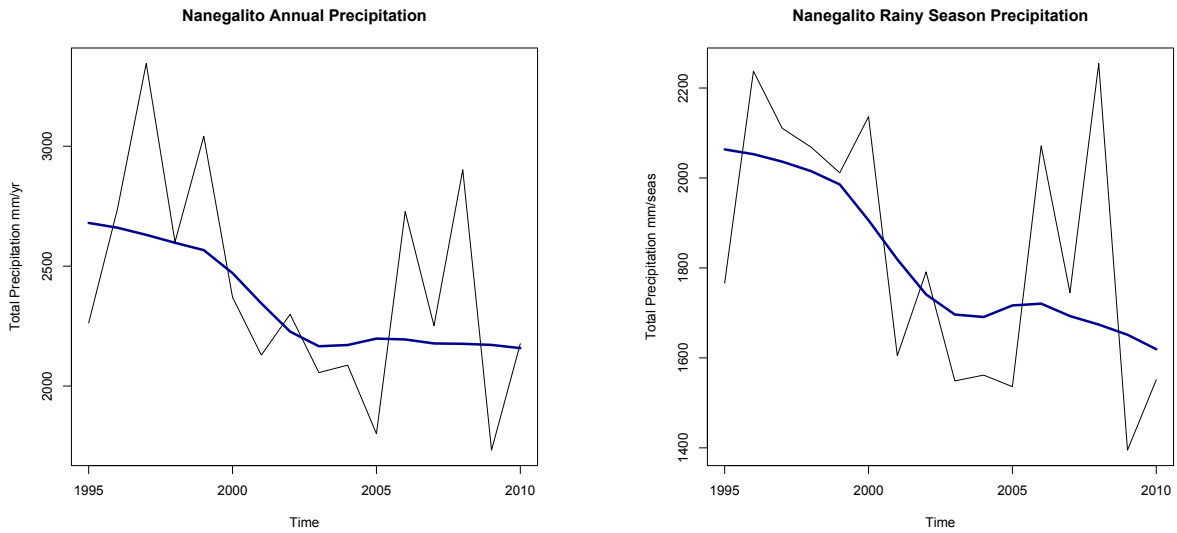
TABLE 7

Potentially decreasing precipitation trends at Nanegalito 1995-2010

NANEGALITO (M339)		
Precipitation Trends: 1990-2010		
Annual	Rainy Season (Dec – May)	Dry Season (June – Nov)
-238 mm/decade	-121 mm/decade	no trend

FIGURE 9

Potentially decreasing precipitation trends at Nanegalito 1995-2010



3.2 Climate Model Skill and Bias

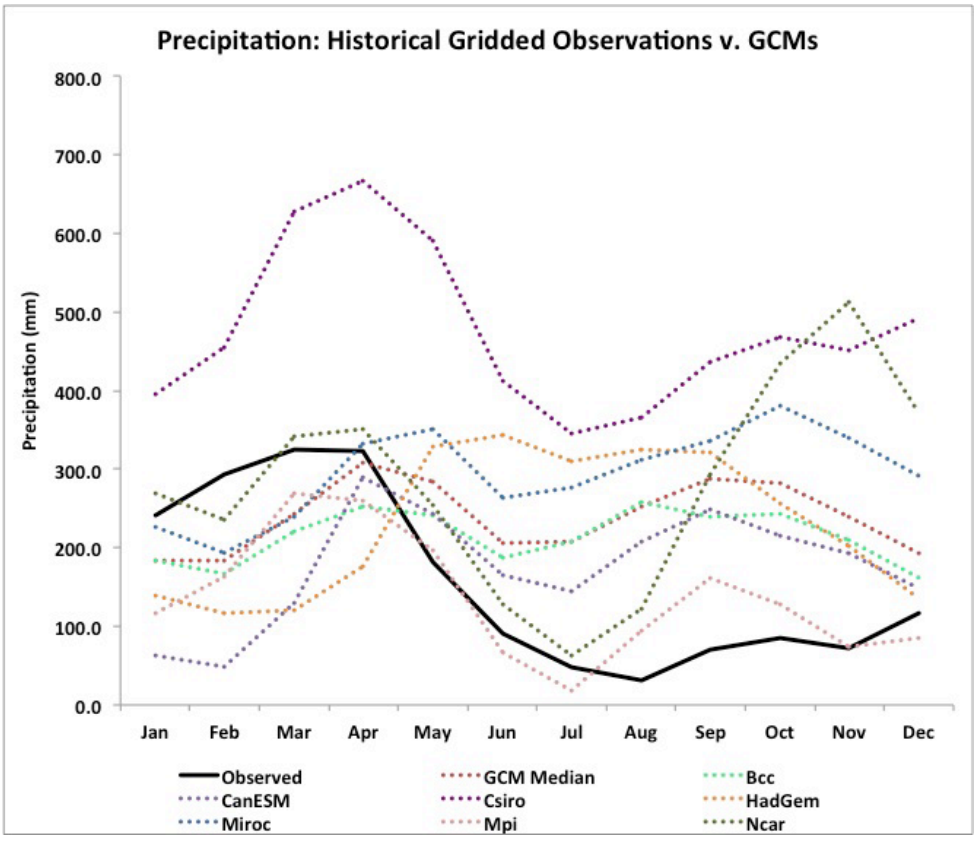
The CMIP5 climate models were evaluated for their ability to broadly replicate historical precipitation and temperature characteristics for the study area, and to identify model biases, over a standard 30-year time period of 1976-2005. The end year, 2005, represents the stopping point of the historical CMIP5 simulations. Taylor Diagrams were constructed to visualise three skill scores—correlation, standard

deviation (variability) and root-mean-square error (RSME)—when comparing seasonal and annual statistics between the models and the observations. *Standard deviation* is a measure of the area's climate variability, due to both natural processes and climate change. A model should be able to do a decent job of replicating variability, but will always over- or under-represent variability because the scale of the model grids is larger than our study's grid scale. Another metric of model skill is the *RMSE*—how far the model's simulated squared mean value is on average from the observation squared mean value. Models clustered close to the observation point perform well across the measured skill scores. The farther the model is from the observation, the poorer its ability to replicate key observational statistics.

The majority of the climate models (Figure 10) tend to have a wet bias in most months, particularly those corresponding to the dry season. In many of the models, the onset and withdrawal of the observed rainy season are shifted and two rainy seasons are seen—(1) March to May and (2) August through October. For those individual, higher elevation stations with a bimodal rainy season, some of the GCMs are better able to replicate historical statistics. The models exhibit a warm bias in monthly minimum and maximum temperatures (not shown), and also have an inverse seasonal relationship with the observed temperatures.

FIGURE 10

CMIP5 GCM simulated median monthly precipitation compared with the observed median monthly, spatially averaged precipitation over the entire downscaling region [-79.75 to -78.25W: -1.25 to 1.25N]. Period of comparison of models rainfall regimes with observation is 1976-2005.



The tendency of the GCMs to overestimate/underestimate precipitation on monthly time steps also impacts their performance at seasonal and annual time steps, as displayed in the Taylor Diagrams.

1. The median ensemble member of all of the GCMs is reasonably correlated (statistically significant at the 95th percentile) with the median observed precipitation value during the dry and wet seasons (wet: 0.43 and dry: 0.41). On an individual basis, the models tend to be weakly or negatively correlated with observation value. This is a reflection of their overestimation/underestimation of precipitation and placing the timing of the precipitation in the wrong months. Those models that simulated two prominent rainy seasons have the most negative correlation.
2. Miroc and Csiro do the best at capturing the large precipitation variability within a year and on an inter-annual basis. The median model ensemble member and Bcc, Ncar and Mpi under-represent variability by a third on an annual and seasonal basis.
3. The centred RMSE difference between the models and the observation ranges between 200mm to 500mm depending on the season. This is again a reflection of the models' inability to capture the large observed precipitation variability.

Similar model biases and lack of skill are also evident in replicating historical minimum and maximum temperature statistics (refer to Figures 11 to 13) and seasonality (a slightly cooler period during the dry season).

The CMIP5 model bias, poor correlation with the observation values, and inability to replicate the natural variability is also corraborated by previous studies on the performance of CMIP3 models for the Rio Paute Basin in southern Ecuador (Mora et al. 2012). The CMIP3 models are the prior generation of GCMs used by the international climate modelling community and informed the IPCC Fourth Assessment Report; the CMIP5 models are built off of the CMIP3 models. Mora et al. compared the performance skill for a greater number of GCMs than we were able to do in the limited time frame of this study, and found similar results of poor performance across 23 models as the seven models we were able to test. Their analysis also revealed that the GCMs, and even two higher resolution models, are currently unable to replicate historical monthly and seasonal precipitation and temperature characteristics well for the complex topography of the Ecuadorian Andes regions and the foothills leading up to them. Mora et al. also concluded "a strong increase in the climate model spatial resolution does not necessarily result in more accurate description of local climate properties" (p1). Other studies report substantial precipitation biases in the tropics in many CMIP3 and CMIP5 models, with a strong wet bias noted in the CMIP5 models over equatorial Latin America (Randall et al. 2007; Flato et al. 2013).

Given the individual models' poor performance in replicating the study domain historical statistics for precipitation and temperatures, we decided to use the multi-model mean (MedEns henceforth) for downscaling and generating the future climate change projections.

Use of the MedEns over the individual models:

1. is more robust and less biased in the historical simulations than the individual models;
2. reduces the undue influence of the more biased models; and,
3. still captures a possible range of climate change in the four-parish region and broader domain.

We downscaled the MedEns RCP4.5 and RCP 8.5 for each of the three future time periods: 1) the 2020s - 2010 to 2039; 2) the 2050s - 2040 to 2069; and, 3) the 2070s - 2060 to 2089. This allowed evaluation for potential diversions in rates of climate change between the medium and pessimistic scenarios. As mentioned in Section 2.1.5, not all seven CMIP5 models had data available on the PCMDI data portal through the year 2100 due to updates to the portal. The MedEns was therefore compiled from fewer models than the full seven for the 2050s and the 2070s (see Table 8).

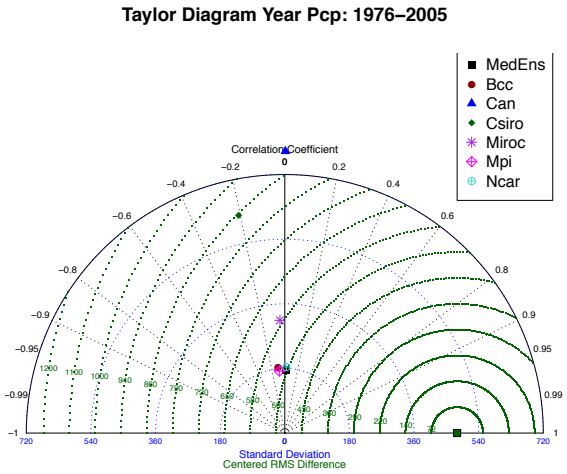
TABLE 8

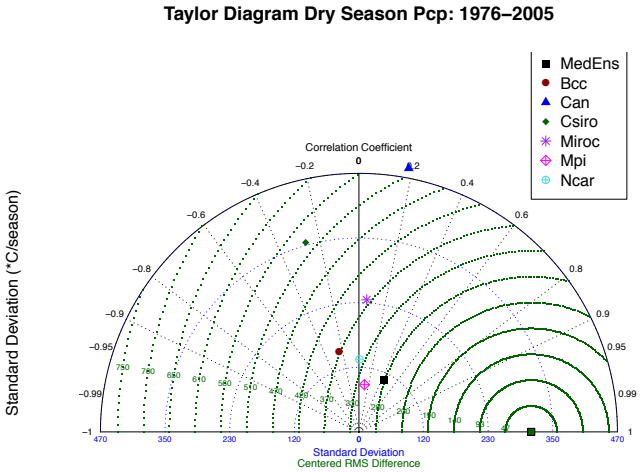
CMIP5 models used to form the MedEns member for downscaling in three future time periods.

2020s: 2010 – 2039	2050s: 2040 – 2069	2070s: 2060 – 2089
Bcc CSM1.1M	CanESM2	CanESM2
CanESM2	Csiro MK3.6.0	Miroc ESM
Csiro MK3.6.0	Miroc ESM	
HadGEM2-ES	Ncar CSSM4	
Miroc ESM		
Mpi ESM-MR		
Ncar CSSM4		

FIGURE 11

Taylor Diagrams of GCM's skill scores at replicating historical precipitation statistics over the period 1976-2005





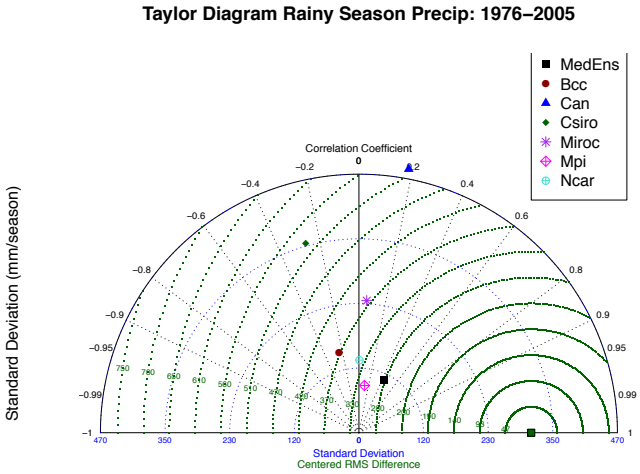
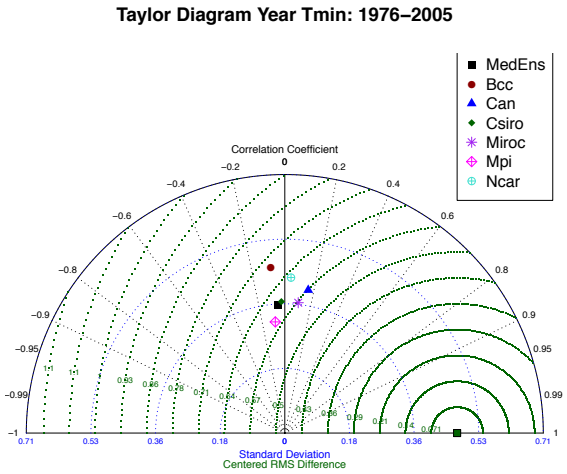
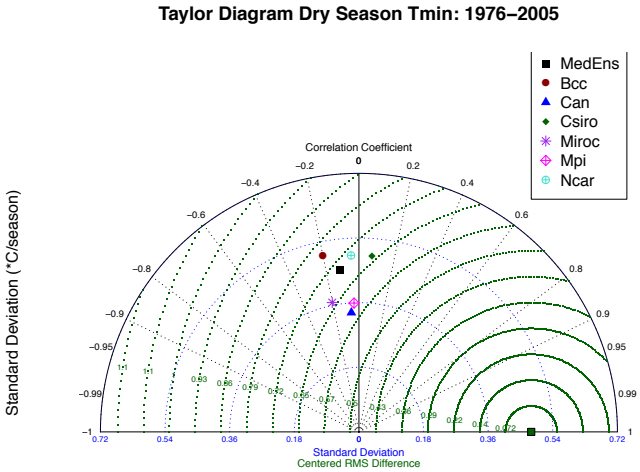


FIGURE 12

Taylor Diagrams of GCM's skill scores at replicating historical minimum temperature statistics over the period 1976-2005





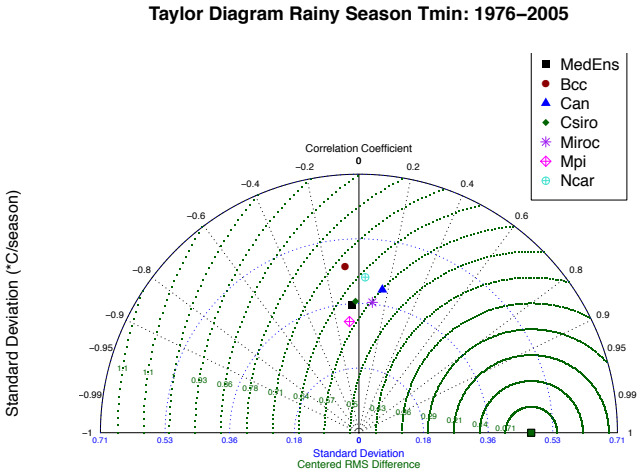
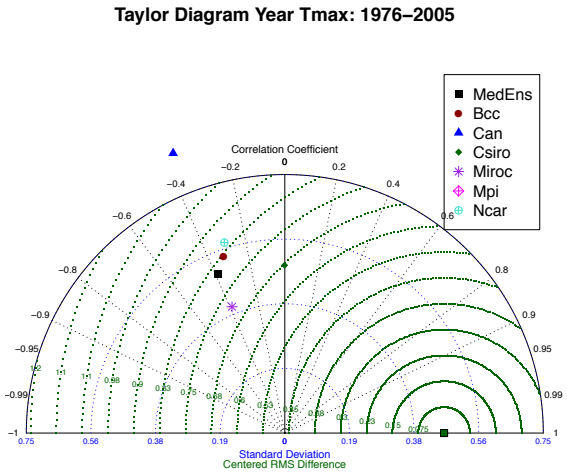
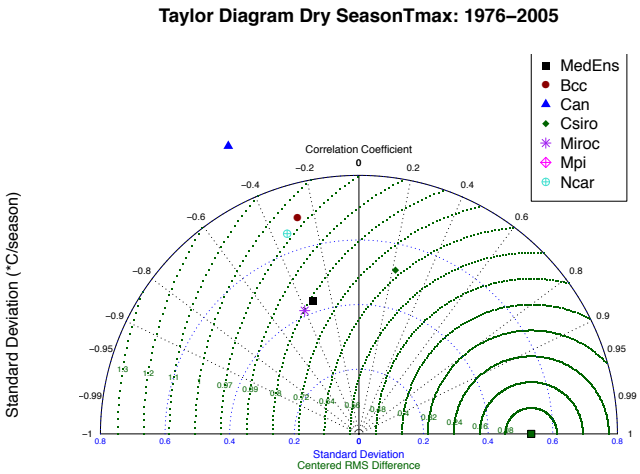
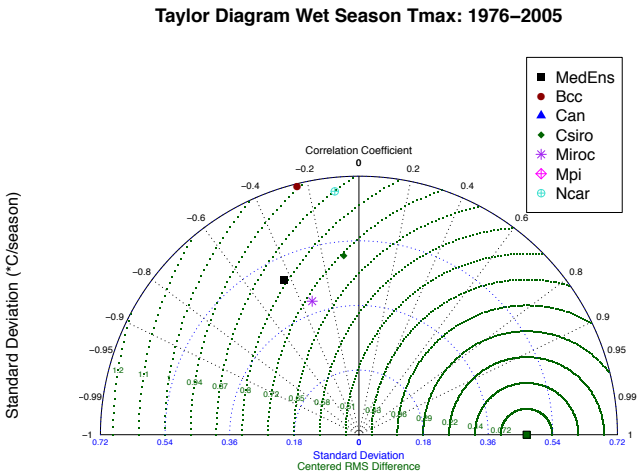


FIGURE 13

Taylor Diagrams of GCM's skill scores at replicating historical maximum temperature statistics over the period 1976-2005







3.3 Future Climate Change Projections

The downscaling revealed that minimum and maximum temperatures, and precipitation are likely to increase in all seasons for the downscaling domain. Over the four-parish study area in particular, the following potential changes are possible:

TABLE 9

Projected changes (per cent difference) in precipitation in Grid 15 for three future time periods when compared with the past (1976-2005)

Annual	Rainy Season	Dry Season
Short-term 2020s: 2010 - 2039		
36 to 40% +	22 to 24% +	64 to 82% +
Mid-term 2050s: 2040 - 2069		
42 to 43% +	31 to 32% +	69 to 74% +
Long-term 2070s: 2060 - 2089		
12 to 39% +	6 to 24% +	17 to 60% +

Precipitation is likely to initially increase most over the short (2020s) and medium (2050s) term, with increases greatest during the dry season. However, the models are projecting that the increasing precipitation trends may begin to reverse during the long term (2070s). There are several possible explanations for the behaviour projected in future precipitation for the different epochs; a combination of each explanation may factor into the overall projections:

1. The first possible explanation is that the projections generated for the 2070s are drawn from a smaller subset of CMIP5 models (only two). Using fewer models to craft the MedEns will not adequately capture the broader range of possible change.

2. Most of the models exhibited a wet bias during all seasons over the historical period 1976-2005. The equidistant quantile matching correction method was applied to the future projections to reduce the wet bias carrying forward, but also allow for non-stationarity and the potential increase in precipitation. Some of the models' wet bias will continue to manifest through the future climate change projections.

3. The GCMs did capture the bi-modal rainy season regime that is exhibited at some of the higher elevation stations, but were unable to replicate the single rainy/dry season seen at the lower elevations. The seasonal distribution for downscaling was pegged to the demarcations of the lower elevation stations, but the bi-modal seasonal bias will be partially carried through the projections.

4. The trend is real. Over the near future, precipitation rates to increase substantially more than in the medium and long-term. As warming continues over the equatorial region, there might be an overall decreasing trend in precipitation over the longer term.

TABLE 10

Projected changes in minimum temperatures in Grid 15 for three future time periods when compared with the past (1976-2005)

Annual	Rainy Season	Dry Season
Short-term 2020s: 2010 - 2039		
1.1 to 1.2°C +	1°C +	1.1 to 1.2°C +
Mid-term 2050s: 2040 - 2069		
2.5 to 2.9°C +	2.3 to 2.6°C +	2.6 to 3°C +
Long-term 2070s: 2060 - 2089		
2.5 to 3.5°C +	2.2 to 3.2°C +	2.6 to 3.6°C +

TABLE 11

Projected changes in maximum temperatures in Grid 15 for three future time periods when compared with the past (1976-2005)

Annual	Rainy Season	Dry Season
Short-term 2020s: 2010 - 2039		
0.8 to 1.1°C +	0.9 to 1.1°C +	0.8 to 1.3°C +
Mid-term 2050s: 2040 - 2069		
2.1 to 2.2°C +	2.1 to 2.3°C +	1.8 to 2°C +
Long-term 2070s: 2060 - 2089		
3.3 to 4.8°C +	3.1 to 4.4°C +	3 to 4.3°C +

For both minimum and maximum temperatures, there is a strong possibility for substantial warming by the end of the 2070s in the four-parish study area. Minimum temperatures are likely to increase more than maximum temperatures in the 2020s and 2050s, with warming most pronounced in the dry season. The increasing temperatures, particularly in the dry season, were also projected in the Rio Paute Basin, in southern central Ecuador (Mora et al. 2014), lending some confidence to this investigation's projections.

FIGURE 14

Spatial annual precipitation patterns for northwest Ecuador for three time periods: Historic, the 2020s and the 2050s.

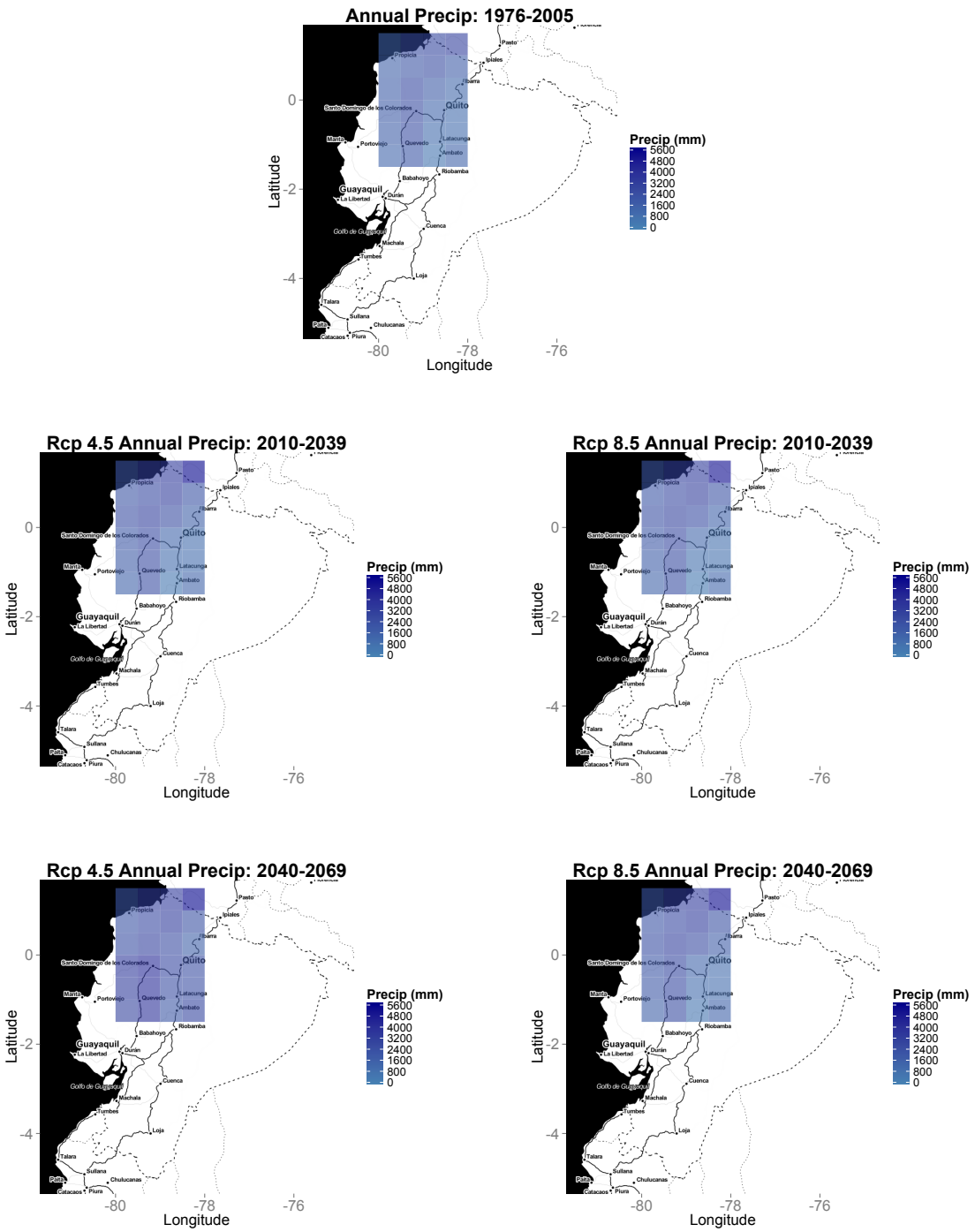


FIGURE 15

Spatial annual maximum temperature patterns for northwest Ecuador for three time periods: Historic, the 2020s and the 2050s.

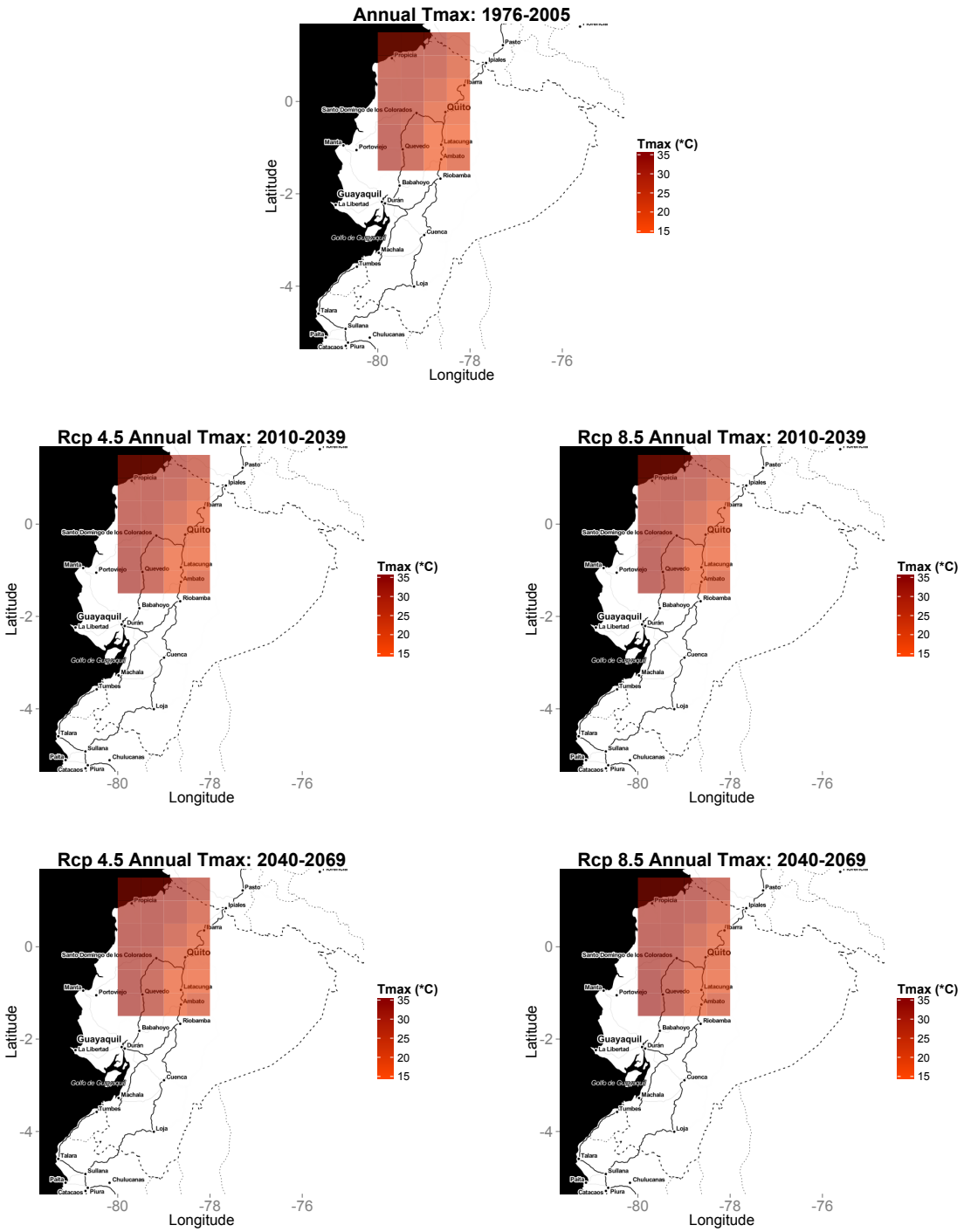
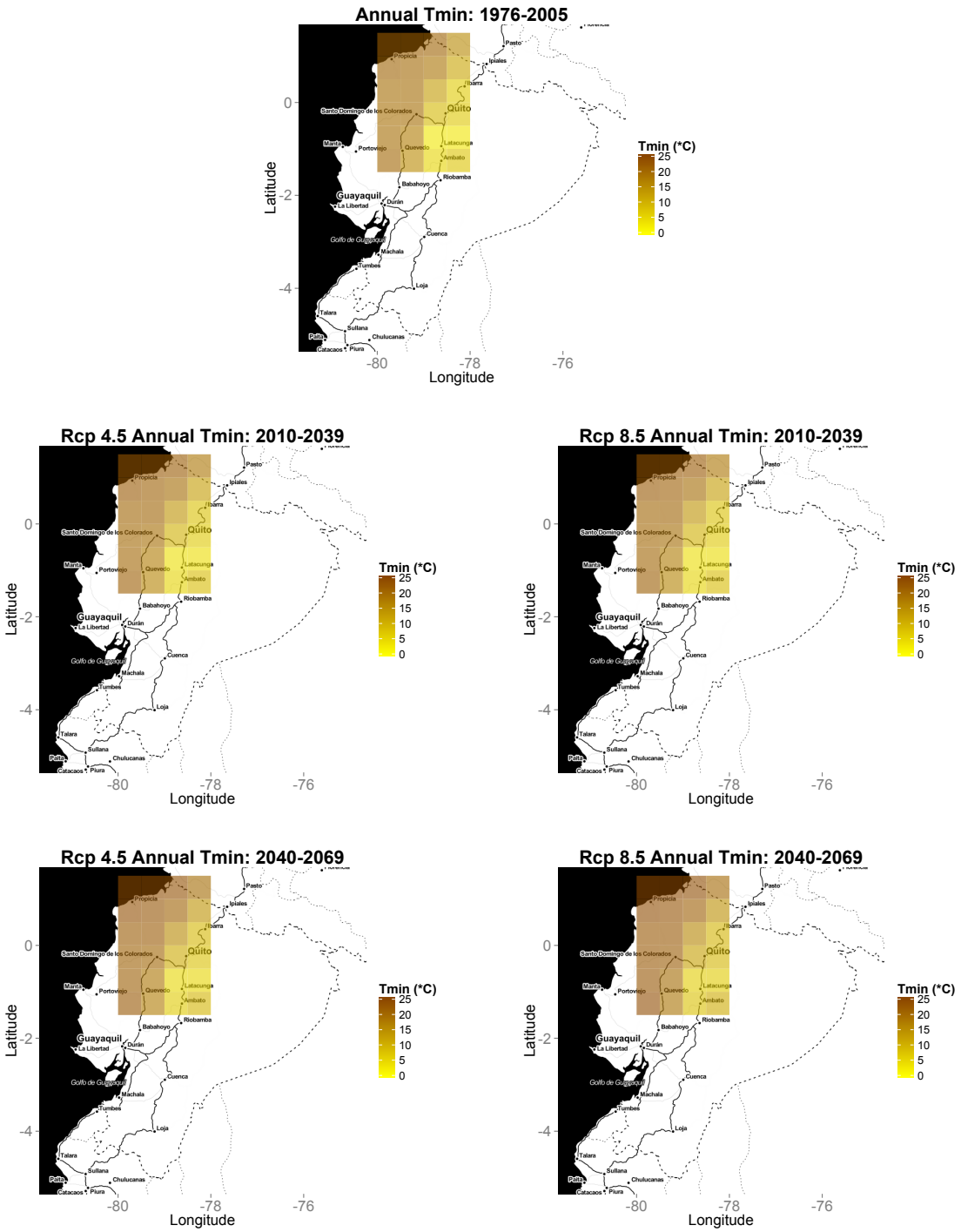


FIGURE 16

Spatial annual minimum temperature patterns for northwest Ecuador for three time periods: Historic, the 2020s and the 2050s.



4. Potential Implications for Climate-Vector Risk

The climate change analysis here could not conduct an in-depth investigation of daily rainfall data and temperature conditions as has been done for the Rio Paute Basin in the southern Ecuadorian Andes (Celleri et al. 2007). The Rio Paute Basin covers approximately ~5000 km^2, and has high topographical variability with elevations ranging from 1840 to 4680 m. In that basin, and in a separate study, climatologists found that there is extreme spatial variability in rainfall and rainfall regimes—with daily precipitation amounts up to 25% different at locations only 4 km away from each other and station elevation determining whether the station had a single or bimodal rainy season regime (Celleri et al. 2007; Buytaert et al. 2006). The data situation is also limited in the Paute Basin; however, the authors were able to access sufficient daily rainfall and temperature data for a number of stations up until 1998. They report that more current data are unavailable. Our investigation of climate regimes around the four parishes of Nanegal, Nanegalito, Pacto, and Gualea could not be conducted on the level of detailed analysis as in the Paute Basin. There were simply not a sufficient number of weather stations (spatial density) with good quality daily data to analyze the micro-rainfall regimes at scales of 5 km or less that are likely to be present in the four parishes as in the Paute Basin. We observed significant differences in rainfall regimes according to elevation based on the limited analysis conducted (Section 3) but the records for some of the stations are only 10 to 15 years in length with significant missing data. Therefore, we have to caution interpreting the rainfall regimes as fixed in a uni- or bi-modal rainy season distribution until at least another 15 years of daily or sub-daily observational data are collected. This is the minimum length of time necessary to extend the records to capture localized micro-climatologies.

Given the data limitations in the four-parish study area, what can be said about potential climate change implications for vector-climate risk? It is likely that precipitation and temperatures will increase over the short- (2020s) to mid-term (2050s), with temperature increases continuing into the far future. It is possible that precipitation may begin to decrease by the late period (2070s). Minimum temperatures are expected to increase proportionally more than maximum temperatures. Warming temperatures at all elevations, particularly night-time minimums, may facilitate the upward-elevation spread of certain vectors. The potential increases in precipitation in all seasons may also facilitate outbreaks of particular vectors, if based on analogous observations from historical explorer and administrative records.

Heavy rainfall years and flooding along the coastal areas of both southern and northern Ecuador have been well correlated with strong El Niño events in reconstructed historical records beginning in the late 1500s (Quinn 1993; Arteaga et al. 2006). Explorers and administrators noted epidemics of malaria and yellow fever in Guayaquil and along the Rio Guayas during torrential rain years of 1740, 1842-1844, 1853-1856,

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1867-1869, 1877-1878 and 1880 (Arteaga et al. 2006). These years correspond with reconstructed records of plausible El Niño events. Likewise, extended periods of drought have been noted during La Niña events. Work into establishing relationships between large-scale climate processes like ENSO, the PDO and rainfall in Ecuador's interior regions is on-going. Lack of long-term observation records and spatially sparse observations (as discussed in Section 2.1.2) in much of the interior are the limiting factors in historical climate and future climate change analysis. However, given that outbreak incidences of vector-borne diseases were noted along coastal regions during abnormally wet years in the past, it is plausible that there might be increasing vector presence in the mid-land regions where the four parishes are located in wet years, particularly those that correspond with strong El Niño years and/or positive phase PDO.

It was beyond the capacity of this study to evaluate potential climate changes to the frequency, intensity, and cyclical and spatial shifts in large-scale climate phenomenon like ENSO, the PDO and the Madden-Julian Oscillation (another climate pattern) that influence rainfall timing, spatial distribution and amounts in Ecuador. From a policy and public health perspective, there is enough evidence to know that heavy rainfall years can trigger outbreaks of vector-borne disease throughout Ecuador. Such years tend to correspond with strong El Niño events, which when reinforced by a positive phase PDO, might provide enough warning to begin preparing public awareness campaigns and mobilising health facility and medical resources in anticipation of potential outbreaks.

5. Recommendations for Future Work

The climate is changing throughout Ecuador, but it is not yet possible to attribute a high degree of certainty to the range of potential change in precipitation and temperatures for many parts of the country. Trying to project micro-level change at scales of ~5 km to 10 km is even more risky given the lack of sufficient observation data collected at stations of a high enough spatial density. A few regions of the country, such as the coastal regions around Guayaquil or the Rio Paute Basin, may have a good enough density of weather stations to construct historical high-resolution (~5 km to 10 km) gridded climate datasets for use in climate risk and impacts studies. Even in regions with a greater density of stations, stations need to be better maintained to ensure the collection of sub-daily weather data and the records appropriately collated, quality-controlled and digitized for the public domain.

Additionally, in areas with highly complex terrain, such as the four parishes in northwest Quito Canton, it would be ideal to develop reanalysis gridded datasets using a dynamic weather simulation model that is based on local physical processes combined with observation data, similar to ERA-Interim datasets. The ERA-Interim is a global atmospheric reanalysis project combining the Centre for Medium-Range Weather Forecasts (ECMWF) model with observations to generate gridded climate data (Dee et al. 2011). If the weather simulation model is run at a high enough resolution (~5 km) and verified against available observation data, a more robust gridded climate dataset could be used for future analysis in numerous disaster risk reduction, ecological, health and climate adaptation planning studies and programs. Such a product is likely to be more robust, being based on physical processes and verified against quality-controlled observation data than statistically gridded datasets like WorldClim or the one produced for this study.

The World Meteorological Organization is working with meteorological administrations globally to develop the Global Framework for Climate Services (GFCS, see http://gfcs-climate.org/ as accessed on 12 February 2016). The GFCS contains a number of action item areas to facilitate the development of climate services in each country to support the provisioning of climate information in policy planning (e.g., health, agriculture, water, energy and climate change adaptation), private sector and academic applications. We recommend the following actions be undertaken to improve the quality and accessibility of climate observation data for Ecuador, as part of a broader climate services program.

TABLE 12

Climate Services Action Area Recommendations

Action Area 1: Monitoring
• Installation of automated weather stations in more rural parish locations, particularly in the mid- and high-elevation regions to capture diverse micro-climates • Coordination on station data reporting between formal institutions • Working with amateur citizen meteorologists who might be operating private, home-based weather stations • Installing automated weather stations at middle and upper-grade schools and providing scientific training and capacity building programs to the students and teachers for maintaining the station and reporting data. Such programs provide additional job skills to students and build their long-term capacities and awareness around climate change
Action Area 2: Collaboration
• Coordination on station data reporting between formal institutions • Working with amateur citizen meteorologists who might be operating private, home-based weather stations
Action Area 3: Data Collection and Accessibility
• Collating all existing data for each station on a station basis and cleaning the station record so that one consistent dataset is available per station. Currently, station data are available across a broad array of international sources (e.g., Global Historical Climatology Network, World Weather Reports, etc.)—but the reported values are different in each source • Running and reporting standard data quality checks (e.g., homogeneity, outliers, sequences of repetitive data, etc.) and providing station metadata indicating if station moved, new equipment was installed or other shifts that can influence data collection • Making station data publicly available in digitized forms beyond the Anuario documents. Small fees could be charged as revenue generation for accessing the data to recover costs, if permissible within existing institutional mandates and regulations • Constructing a reanalysis gridded climate dataset, similar to the ERA-Interim project in Europe

Endnotes

1 Weather station data have to be checked for non-homogeneity. Non-homogeneity, or artificial trends, may be introduced into station data if the station is moved one or times; trees or buildings are planted or constructed nearby the equipment and influence the measurements; a city grows around a station and introduces an "urban heat island" or warming trend; or other human influences artificially influence the data.

2 These datasets are more easily validated and verified in the United States and parts of Europe. Further research is necessary by the climate science community to validate emerging 'high-resolution' climate datasets against observational data in many other countries. This will be possible only over time as more stations are added, records are digitised and cleaned, and stations are in operation for a minimum of 30 years to establish climatologies.

3 Now National Centers for Environmental Information NCEI

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Sub-Component Study:
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for

Climate Vulnerability of the Health Sector in Quito: Making Technical Data Accessible to Policy Makers

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