CONTRIBUTION OF VARIABLE RENEWABLE ENERGY TO INCREASE ENERGY SECURITY IN LATIN AMERICA

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EXECUTIVE SUMMARY

The emergence of variable renewable energy in the global energy landscape has generated major challenges in both the long-term planning and the day-to-day operation of electrical systems. Although many Latin American (LA) countries have successfully used renewable resources such as water for electricity generation for many decades, there is much less detailed knowledge about the solar and wind resource behavior as they depend on local climate variables and on global atmospheric patterns that had not been studied in the context of electricity generation.

Additionally, the direct interaction between these three resources, sun, wind, and water, becomes much more relevant now that many countries are seeking to diversify their energy matrices, either to reduce their dependence on fossil fuels or to reduce pollution and greenhouse gas emissions associated with their use. Governments see in these resources a very attractive option to expand their generation capacity by the advantages they currently offer in terms of long-term electricity price stability and very low carbon footprint. However, climate change has introduced an additional uncertainty in their long-term management since the global increase in temperatures can have direct effects on the availability of these resources and therefore on the electricity generation from them.

These aspects have been scarcely studied in Latin America. Therefore, the analysis presented here aims to shed some light on a successful integration of variable renewable energies to electricity networks and how, despite depending on the fluctuations of the climate itself, they can also contribute to the energy security of the region.

The study is divided in two sections. The first part of this report presents a review of the latest state-of-the-art variability indices for wind and solar energy, as well as a survey of existing studies addressing complementarities between renewable resources. One of the most relevant indexes for the financing and operation of variable renewable energy plants is the Interannual Variability. The study calculates this parameter for the regions with the highest solar and wind potential in Latin America (called throughout the report hotspots) and then performs a statistical analysis to evaluate the complementarity between hotspots using linear correlations.

The data used for the analysis come from the IDB’s Grid of the Future project, which evaluated for the first time in the region with a detailed and homogeneous methodology the characteristics of the solar and wind resource in 21 countries in Central and South America. The database generated from satellite data and validated with more than 700 surface measurement stations was used in the Grid of the Future as an input to optimally determine the share of variable renewable energies in the electrical matrix of these countries by 2050.

Results show a higher variability for wind power than for solar power generation. They also show that Brazil plays a significant role regarding renewable energy integration in LA, since it has the strongest capacity to complement and be complemented by several LA countries.

The second part of the study evaluates the possible impacts of climate change on future wind and solar resources in LA and how these impacts can affect the complementarities between these two sources of electricity.

Initially, this report presents the background on the Representative Concentration Pathways and Global Circulation Models as well as a survey of existing studies addressing Global Climate Change on renewable energies.
This study considers MIROC-ESM-CHEM and HadGEM2-ES General Circulation Models (GCMs) and two Representative Concentration Pathways: ii) the RCP 4.5 scenario that represents a stabilization scenario in which total radiative forcing\(^1\) is stabilized before 2100 and ii) the RCP 8.5 scenario that represents increasing greenhouse gas emissions over time.

The climate projections for the IDB database were made based on HadGEM2-ES – GCM since this model was the one that best replicates the historical database of wind speed and solar irradiation. Based on these climate projections, the complementarity between hotspots was re-evaluated.

RCP 4.5 is a scenario of intermediate mitigation, with a lower concentration of greenhouse gases in the atmosphere than the RCP 8.5 scenario; therefore, as expected, the impact of climate change in the historical complementarities of the analysed regions was lower. The RCP4.5 scenario presents favourable results for the complementarities of most pairs of regions; in only five pairs of hotspots (16%) the complementarities were lower than the historical values.

In the RCP8.5 scenario the complementarity is maintained or improved between 2010-2070 in most of the complementarities analyzed. However, this trend is highly reduced in the last period of the projection (2070-2100). Regarding the long-term planning in the power sector this result could encourage the expansion of solar and wind power plants since no strong variation in the energy generation profile is expected due to climate change effects in Latin America.

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\(^1\) Radiative forcing is a measure of the Earth’s energy budget and its equilibrium. If the subtraction of the energy flowing out of the planet from the energy flowing in, is different from zero and positive, there has been some warming (or cooling, if the number is negative).
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SECTION I

Analysis of the value of wind and solar energy
01. Introduction

Renewable energy or, more specifically, wind and solar, are commonly known as variable energy sources, given the fact that the energy they produce varies over time and is highly dependent on geographic location. This variability is a consequence of the dependence on weather and climatic conditions [Anjos et al., 2015]. At the same time, the variations of solar and wind energy output generally do not match the time distribution of the energy load demand [Anjos et al., 2015]. Integrating renewable energy into existing networks poses significant challenges. Addressing them will require not only regulatory changes to existing frameworks, but also detailed knowledge of the physical resources, their variability and possible complementarities.
There are several issues related to integrating large-scale power supplies from renewable energy sources into electrical power systems, such as short-term balancing, the need to back-up power plants and overproduction [Buttler et al., 2016]. The variability of these resources, on the timescale of minutes to hours, impacts load following requirements, while day-to-day variability and longer variations influence day-ahead requirements and long-term regional infrastructure planning, especially at higher penetration levels [Mills & Wiser, 2010].

Uncertainties involved in the prediction of energy production make it difficult to dispatch the electricity at the exact time consumers need it, in contrast to conventional fossil fuel power plants, where the fuel is stored and can be processed almost immediately, providing firm capacity. Integration of higher shares of renewable energy calls for technologies and techniques to manage load demand fluctuations and optimal operation of reserve capacities [Kougias et al., 2016].

This leads to the question of whether an increasing share of variable renewable energies in an energy system based on conventional generation could contribute to providing firm capacity. What is the inter-annual variability of the solar and wind resources in Latin America (LA) and how does this variability behave across the region? Are the solar and wind resources complementary to hydro resources, i.e., do the seasonal patterns of these resources complement each other?

Due to the abovementioned constraints to solar and wind energy, innovative solutions that lessen the variability of energy production is a key point in ensuring the reliability of future energy systems. According to Kougias et al. [2016], as the currently applied techniques (storage capacity, curtailment and reserves in responsive power) imply either additional costs or partial losses of the energy output, other solutions are worth investigating.

This problem may be partially overcome with hybrid solar-wind (also with other renewable sources, such as hydro) power generation systems that integrate two or more energy resources using their complementary characteristics [Anjos et al., 2015]. For such integration, an optimal trade-off between the overall amount of energy produced and its time stability is the objective. This is equal to smoothing out power production, decreasing the instances of high and low values of electricity production. Such approaches will result in energy systems that support safer energy production, involving variable renewable energy in a significant share. Reducing the variability of energy production and increasing its predictability improves the stability of the grid and reduces dependence on high-cost energy storage systems [Kougias et al., 2016].

This report analyses the seasonality and variability of renewable energy resources, as well as possible complementarities between PV solar, wind and hydraulic energy in Latin American countries. The results of this study are an important input to regional energy planning and policy design authorities regarding the contribution of VRE, such as wind or solar energy, to cover future energy demand in LA.
2.1. Review of the state-of-the-art of indices for variability of wind and solar energy

Among the challenges that the unpredictable behavior of renewable sources represents, one is to define a suitable place that will ensure a profitable project. This often requires a detailed, and sometimes costly, analysis of the local meteorological conditions [Ritter et al., 2014].

Since the variability of large scale wind or solar power generation depends on several factors – which include geographic dispersion and weather regimes, the characteristics of the power plants, the size of the area covered by the wind turbines or solar panels of the renewable power plant, etc. [Kiviluoma et al., 2014] –, the use of location-only measurements, such as the local average wind speed or the average local solar irradiation, is not enough to establish an accurate foresight of the production of energy from these resources. As a result, some studies have tried to establish new approaches to assess the local wind and solar potential and its variability [Hammer et al., 2005; Hodge et al., 2012; Kiviluoma et al., 2014; Skartveit et al., 2016].

Among these approaches, the definition and application of indices has been commonly used as a way to estimate long-term values for the variables in question.
The indices used in this kind of analysis describe the fluctuations of the resource or of the energy generated from a power plant (e.g. a wind farm or solar plant) throughout its life span [Ramírez, 2014]. The literature presents several types of indices. Among them, there are simple ones like the long-term variability index (Merra-based wind and Solar index) used by Ramirez [2015], in which the annual wind power generation (APW) per year is compared against the 100% value (or long-term value). The 100% value represents the calculated mean of the annual wind power production for each site within the time horizon. Therefore, this index represents how variable is the annual wind power generation when compared to the long-term value.

Another commonly-used index is the IAV (Inter-annual Variability). The IAV quantifies how much a yearly value differs from the long-term average value. It is a key input to the assessment of wind and PV projects, as it can influence the debt-ratio and the return on investment (ROI) of a project [Darez et al., 2014].

The definition of the IAV is given by Eq. (1):

\[
IAV = \frac{\sigma(x)}{\mu(x)}
\]

where \(x\) is the yearly mean value of the chosen variable (GHI, Wind Speed, River flow, etc.), \(\sigma(x)\) is the standard deviation of \(x\), and \(\mu(x)\) is the mean value of \(x\). If we consider, for example, the annual mean GHI at a site, the IAV will quantify statistically the likelihood of the mean value of one year deviating from the long-term mean at that site. Mathematically, three years of data is enough to calculate the IAV. However, a three year period is unlikely to be representative of the long-term value [Darez et al., 2014]. According to The Crown State [2014], a true estimation of inter-annual variation ideally requires 50 or more years of local measurements.

An alternative to the IAV index is the Inter-monthly Variability (IMV). Its definition is similar to the IAV definition of Eq. (1), with the difference that in this case the variable refers to a monthly mean value. This index, as expected, can be much higher than the IAV for the same spot due to several reasons, such as annual weather patterns that do not always fall in the same month, lower time window or random events over the course of the year.

The IMV index, however, is not usually considered during the financial analysis, but as a metric for utilities to understand grid stability [The Crown State, 2014]. In Darez et al. [2014] this index is used to evaluate seasonal variability, since it is important to understand the magnitude of the expected fluctuation from season to season. The above indices can be applied to the resources themselves (wind speed, GHI etc.) or to the energy generated from these resources. In the following sections specific variability indices for wind and solar energy will be presented.

2.1.1. Variability Indices for Wind Energy

The literature presents indices that are more sophisticated and specific to wind energy. The combination of a wind index and production data for existing wind farms can supplement or replace site-specific wind measurements [Rimpl et al., 2011]. The indices associated with wind energy can be classified based on the parameter to which the variability analysis will be applied.

- Wind Energy Production Index

The Wind Energy Production Index (WEPI), also known as Energy Yield Production Index, which is the most commonly used index. It is based on many years of operation. As mentioned, an index can be used to calculate the long-term value and, in this case, the long-term average energy yield is calculated by scaling the energy yields of already installed wind turbines; in other words, the monthly or yearly measurements of wind data are extrapolated to long-term periods. The yearly or monthly energy yields are presented as relative values compared to the long-term reference [Winkler et al., 2009]. Wind indices are also used to monitor existing wind farms in order to establish whether any variations in energy productivity are due to deficiencies in wind turbine performance or wind speeds are below the expected levels. In this sense, wind operators by giving them long-term or even short-term data that would allow them to affirm that their machines were operating according to the expectations [Rimpl et al., 2013]. The scaling of the wind energy generation through WEPIs is also used to compare the energy yield predicted before commissioning the power plant, to the energy yield actually achieved, and to carry out plausibility checks on the meteorological data input of energy yield assessments [Winkler et al., 2009].

In this category of Energy Yield Production Indices there is also the German IWET (also called BDB index [Betreiber-Datenbasis, 2011], that is one of the most well-known wind indices, the IWR index [IWR] and the Danish Wind index, others are compared to the long-term values. In this case, the scaling of the wind energy generation through WEPIs is also used to compare the energy yield predicted before commissioning the power plant, to the energy yield actually achieved, and to carry out plausibility checks on the meteorological data input of energy yield assessments [Winkler et al., 2009].

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penetrations of variable generation are one of the most pressing concerns for system operators and planners [Ma- zumdar et al., 2014]. These energy fluctuations need to be handled, most likely with conventional power plants or with demand side measures (demand management), requiring more flexibility from controllable and dispatchable power generating units, in order to keep the system stable [Moarefdoost et al., 2016, Kiviluoma et al., 2012].

The increase in the ramping periods on the conventional grid is also impacted by increasing ramping costs, which can degrade the value of the renewable energy sources. In other words, higher ramping costs can have a significant effect on the dispatch policies of renewable energy sources [Moarefdoost et al., 2016].

The daily clear-sky index is defined by [Moarefdoost et al., 2016]. It can be considered that a ramping up (ramp up) or decreasing (ramp down) its generation from a wind power plant increases or decreases above a fixed threshold in event occurred at time t if the generation from a wind power plant increases or decreases above a fixed threshold in a non-optimal way: 1) increased heat rates and losses in efficiency; 2) increased operation and maintenance costs; 3) increased probability of forced outages [Hamal et al., 2015]. The knowledge of this variability at different time scales is important for improving the design of a solar energy system and operational strategies. For instance, a predicted high variability may suggest an adaptation of the operational planning with the ready deployment of stand-by generation capability.

The theme of solar energy variability has generated a considerable amount of research during recent years. Special attention has been paid to the study of the short-term variability of the PV power output of a single plant due to cloud fluctuations [Marcos et al., 2011; Mills et al., 2010; Perpinin et al., 2013; Van Haaren et al., 2014].

Clear Sky Irradiance
The daily clear-sky irradiance is a metric used to quantify the amount of available solar radiation that reaches the ground. Taken from Stein et al. [2012], it is defined as the ratio of the area under the Global Horizontal Irradiance curve divided by the area under the clear-sky Global Horizontal Irradiance curve. Figure 1 shows examples of days with different values for Variability Index, which will be presented below and the clear sky irradiance.

Clearness Index
In solar variability studies, the clearness index, which moves seasonal and diurnal variability, showing directly the impact of cloud movements, is commonly cited [Widén et al., 2015]. The daily clearness index is defined as the ratio of the daily sum of global irradiance on horizontal surface to the daily irradiance at the top of atmosphere [Muneer, 2004].

The daily clearness index can be used as a tool for operational planning with the ready deployment of stand-by generation capability. Gagné et al. [2016] also found that, when averaging irradiance time-series for a given surface, the aggregated variability decreases with increasing area. The variability reduction also depends on the cloud speed: the faster the clouds move, the smaller the reduction [Gagné et al., 2016].

Vindel et al. [2014] studied the intermittency of daily global horizontal and direct normal irradiation using fractal analysis. According to them, the range of relative variability is higher in the case of the global horizontal than in the case of the direct. Regarding the multifractality of the irradiation, the intermittency is similar for both components at each station. However, this phenomenon is more intense in the mountainous landscape of the site and its influence on cloud formation. Sites where the mountainous landscape induces cloud formation tend to exhibit more variability for a given mean daily clear index than sites where cloud regimes are driven by weather.

In a similar manner, Kang et al. [2015] proposed a new characterization and classification method (the K-POP method) for daily sky conditions by using the daily clearness index and a new metric called the daily probability of persistence (POPOP). POPOP observations differentiate between neighboring instantaneous clearness indices and calculates a probability that the differences are equal to zero [Kang et al., 2015].

Badosa et al. [2015] showed that solar irradiance variability at the diurnal scale can be classified in regimes based on three parameters: daily clear-sky index; solar irradiance variance; and solar variability reduction during the variability of the solar irradiance [Lauret et al., 2016].

Gagné et al. [2016] characterized the solar variability over one year at two sites that are approximately 400 km apart in South-Eastern Canada. The quantification and distribution of the variability were developed using the Variability Index (VI), the daily clear-sky index and the Variability Score (VS). To characterize variability based on time-series data, two main metrics have been used: the Variability Index and the Variability Score. In addition, the daily clear-sky index is used to quantify the cloud-free sky fraction for the day. The Global Horizontal Irradiance variability was characterized at recording periods ranging from 1s to 30s. The Variability Score was shown to be useful in addition to the Variability Index. Gagné et al. [2016] also found that, when averaging irradiance time-series for a given surface, the aggregated variability decreases with increasing area. The variability reduction also depends on the cloud speed: the faster the clouds move, the smaller the reduction [Gagné et al., 2016].

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2.1.2. Variability Indices for Solar Energy
Solar irradiance varies on time scales from seconds to years. The radiation passing through the atmosphere during clear conditions is called clear-sky radiation [Widén et al., 2015]. The output power of PV plants depends on the incident solar irradiance, which can fluctuate as clouds pass overhead. There are additional time-varying factors that affect the power output: the conversion efficiency is dependent on the cell temperature which, in turn, is determined by absorbed radiation, ambient temperature, wind speed and mounting. Depending on the site, nearby or distant obstacles may shade the view of the system and cause the power ramp up or down [Widén et al., 2015].

Equation 3

\[
\text{ramping index (VI)} = \frac{x}{x_{\text{Ma}}} \times 100
\]

where \( x \) is the generation of the power plant.
The indices mentioned in this section for solar and wind resources are listed in Table 1.

### 2.2. Review of existing studies addressing complementarities between renewable sources

Recent studies estimated the complementarity between renewable resources, such as wind, solar and hydropower (Perez & Fthenakis, 2015; Butlter et al., 2016; Anjos et al., 2015; Beluco et al., 2012; Kougiass et al., 2016; Silva et al., 2016). The majority of these studies used measured climatic data series or, when there is a lack of data from meteorological stations, statistical models to calculate the clearness index for different locations over time (Perez & Fthenakis, 2015; Beluco et al., 2012; Kougiass et al., 2016; Silva et al., 2016). Other studies, such as Butlter et al. (2016), used energy output data in complementarity studies, paying more attention to the residual load challenges.

Kougiass et al. (2016) defined the term complementarity as the extent to which energy output from different renewable energy sources is not positively correlated over time. Such complementarity aims to reduce the intermittency of energy production by combining systems that have their min/max energy output at different time periods [Kougiass et al., 2016].

- **Long-term Variability Index (WEPI)**: This index represents the relative wind speed value in comparison to long-term average values. This index considers wind conditions without a consideration for energy aspects, which can be useful to compare the wind variations in a specific region [Rimpl et al., 2013]. This index is calculated from the application of a power curve to wind speed data. Either a standard power curve or that of a specific project can be used. The mean monthly value is calculated in relation to the long-term average.

- **Ramping Index**: Ramping index can be defined as the change in the energy production of a wind or solar PV power plant over two consecutive periods of ∆t. It can be considered that a ramp event occurred at time t if the generation from a power plant increases or decreases above a fixed threshold in a time interval - ∆t [Mazumdör et al., 2014]. This index can be applied in an hourly or sub-hourly time scale and will help understanding the impacts on power system operation.

### Table 1. Indices for solar and wind resources and their description

<table>
<thead>
<tr>
<th>Indices</th>
<th>Resource</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Long-term Variability Index</td>
<td>Wind, Solar</td>
<td>The Long-term Variability Index compares the annual energy production for year to the 100% value. The 100% value represents the calculated mean of the annual wind production for each site within the temporal span. This index represents how variable is the yearly energy production when compared to the long-term value [Ramirez, 2015].</td>
</tr>
<tr>
<td>Inter-Annual Variability (IAV)</td>
<td>Wind, Solar</td>
<td>The IAV is defined as the standard deviation of the annual means divided by the overall mean. The IAV quantifies how much a yearly value differs from the long-term average value. It is a key input to the assessment of wind and PV projects, since it can influence the debt ratio and the return on investment (ROI) of a project [Darez et al., 2014].</td>
</tr>
<tr>
<td>Inter-Monthly Variability (IMV)</td>
<td>Wind</td>
<td>The IMV definition is similar to the IAV, but using a monthly mean value. This index is used to evaluate seasonal variability [The Crown State, 2016].</td>
</tr>
<tr>
<td>The Wind Energy Production Index (WEPI)</td>
<td>Wind</td>
<td>The WEPI calculates the long-term average energy yield by extrapolating the monthly or yearly measurements of wind generation data to long-term periods. The yearly or monthly energy yields are presented as relative values compared to the long-term reference [Winkler et al., 2009]. This index is used to monitor the existing wind farms in order to establish whether the variations in energy productivity are due to deficiencies in wind turbine performance or due to wind speeds below the expected levels.</td>
</tr>
<tr>
<td>Wind Speed Index</td>
<td>Wind</td>
<td>This index considers wind conditions without a consideration for energy aspects, which can be useful to compare the wind variations in a specific region [Rimpl et al., 2013]. This index represents the relative wind speed value in comparison to long-term values.</td>
</tr>
<tr>
<td>Wind Power Density Index</td>
<td>Wind</td>
<td>This index expresses the energy from free wind. This type of index should be used carefully since it can present high variations in comparison to harvestable energy due to the difference between the wind energy potential and technically usable potential [Rimpl et al., 2013].</td>
</tr>
<tr>
<td>Wind Energy Production Index from Wind Data</td>
<td>Wind</td>
<td>This index is calculated from the application of a power curve to wind speed data. Either a standard power curve or that of a specific project can be used. The mean monthly value is calculated in relation to the long-term average.</td>
</tr>
<tr>
<td>Ramping Index</td>
<td>Wind, Solar</td>
<td>Ramping index can be defined as the change in the energy production of a wind or solar PV power plant over two consecutive periods of ∆t. It can be considered that a ramp event occurred at time t if the generation from a power plant increases or decreases above a fixed threshold in a time interval - ∆t [Mazumdör et al., 2014]. This index can be applied in an hourly or sub-hourly time scale and will help understanding the impacts on power system operation.</td>
</tr>
<tr>
<td>Cleanness index (or cloudiness index)</td>
<td>Solar</td>
<td>The daily cleanness index is defined as the ratio of the daily sum of global irradiance on a horizontal surface to the daily irradiance at the top of the atmosphere [Munzer, 2004]. It removes the seasonal and diurnal variability, showing directly the impact of cloud movements.</td>
</tr>
</tbody>
</table>
Intraday Score (VS)

\[
\text{VS} = \frac{1}{n-1} \sum \left( \frac{X_i - \bar{X}}{\sigma} \right)^2
\]

where \(X_i\) is the irradiance at time \(i\), \(\bar{X}\) is the mean irradiance, and \(\sigma\) is the standard deviation of the irradiance.

For a daily basis, the use of this index helps to estimate the necessity of the energy production system (or from potential locations) for the changes in the clear sky index [Lauret et al., 2016]. The VI is defined as the ratio of irradiance time-series curve length between solar PV plants and the useful length of their connecting cables. Hence, the VI is a standard deviation of the difference between the maximum irradiance and the minimum one, measured for the PV plant on an annual basis [Silva et al., 2015]. The Pearson coefficient is calculated as a widely used index to represent correlation and investigate long-term correlations. The values correspond to the scaling exponent \(\alpha\), which can be useful in the analysis of long-term patterns of solar PV systems as a function of irradiation on a daily basis [Perez & Fthenakis, 2015].

The scaling exponent \(\alpha\) is an extension of the Hurst exponent to random processes with varying scales of correlation [Anjos et al., 2015]. The DFA exponent is defined by applying a detrended fluctuation analysis (DFA) on wind speed and solar irradiation time series data from two specific plants, the Souza da Silva Island, Brazil. The DFA method is used to study long-term correlations. The results showed that the correlation coefficient can be considered as a function of the correlation distance as the distance, between a pair of geographic locations, increases. Therefore, they estimated the size and shape of the region across which solar PV must be spread in order to achieve the necessary energy production [Buttler et al., 2016].

In order to estimate the distance from which the variability correlation between monthly PV energy production from two different PV plants appears and the size of irradiance variability correlation between PV systems and small hydropower plants and PV system, the authors calculated the distance from which the variability correlation between the monthly energy production from PV systems and small hydropower plants and PV system is significant. Then, an area analysis of the intraday energy production from the interconnected system began from which the variability correlation between the monthly energy production from PV systems and small hydropower plants and PV system is significant. Finally, an area analysis of the variability correlation between the monthly energy production from PV systems and small hydropower plants and PV system is significant.
Buttler et al. [2016] showed a high smoothing effect in wind power systems by geographic spreading, which indicates a strong decrease in the correlation coefficient as distance between sites increases. On the other hand, the results showed a high correlation of solar PV power production in Europe, between different regions, thus, they conclude that the smoothing effect of solar PV power is limited. Figure 3 shows the difference between the trend in wind and solar PV correlation coefficients with geographic spreading. The main reason for the limitation in the smoothing effect of solar PV power lies in the east-west extension of Europe, different from the Americas, which has a north-south extension. According to Perez & Fthenakis [2015], the east-west extension is not good for the region to have PV systems spread due to the stochastic variability of solar power, that spreads faster in a north-south direction, so an east-west spread of solar PV would not result in significant gains in complementarity.

From the point of view of the load, Buttler et al. [2016] found a low positive correlation between wind power and electricity demand, with a correlation coefficient of 0.25 for Europe. The correlation coefficient between solar PV and the load is also positive, although it has a reduced significance due to night hours (there is no sun but there is a significant energy demand), and a high correlation during daytime. There was a negative correlation between wind and solar PV power production, in the range of -0.04 to -0.26 for all available national data and -0.24 for the whole of Europe. The main difference between Buttler et al. [2016] and other above-mentioned studies is that the analysis of Buttler et al. was made only for existing systems and did not take into account the potential resources (using climatic data). Regarding climatic data series, not only existing systems should be analyzed, but also the potential for renewable sources, assessing if the complementarity between wind and solar could be higher. Another particular approach made by Buttler et al. [2016] was to analyze the load and its relation to wind and solar energy. It would be ideal if the load would correlate with available renewable resources. However, as this is unlikely to happen, it is important to analyze how renewable energy sources would better correlate to each other in order to meet load demand. With the goal of producing energy to meet the required energy for end-use consumers, there is no need for a perfect anti-correlation between solar and wind, but an anti-correlation that allows these energy resources to follow, and meet, the load. The Table 2 shows some aspects of the complementarity studies mentioned in this section.

**Table 2. Aspects of the studies of complementarity**

<table>
<thead>
<tr>
<th>Authors</th>
<th>Study Overview</th>
<th>Complementarity analyzed</th>
<th>Location</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fthenakis [2015]</td>
<td>This research examined over 1.4 million unique pairs of sites in the Americas to quantify the influence of each pair’s geographic separation and bearing on the correlation between the clearness index at different timescales. In addition, this study examined the trends in decorrelation when the distance between the locations changes. Therefore, they estimated the size and shape of the region across which solar PV must be spread in order to reduce its unpredictable variability.</td>
<td>Solar PV - Solar PV</td>
<td>Americas</td>
</tr>
<tr>
<td>Perez &amp; Fthenakis [2015]</td>
<td>This research into complementarity between PV systems and small hydropower plants developed an algorithm that examines the degree of complementarity between different systems in any geographic location. The algorithm also analyzes what can be changed in the installation characteristics of the solar PV systems, in order to increase the complementarity. This iterative optimization process is repeated several times, changing the threshold values of the solar PV energy output in order to explore possible gains in complementarity.</td>
<td>Solar PV - Small Hydropower Plants</td>
<td>Any location</td>
</tr>
<tr>
<td>Anjos et al. [2015]</td>
<td>Used Detrended Fluctuation Analysis (DFA) method to quantify and compare correlations between wind speed and solar irradiation time series for the Fernando de Noronha Island, Brazil.</td>
<td>Wind - Solar PV</td>
<td>Fernando de Noronha Island, Brazil</td>
</tr>
<tr>
<td>Buttler et al. [2016]</td>
<td>The goal of this study was to quantify the variability of wind and solar PV power and the resulting challenges for the residual load in European countries in order to support the discussion about the integration of renewable systems. The main difference between Buttler et al. [2016] and other complementarity studies is that their analysis was made only for existing systems and did not consider potential resources (using climatic data). Another particular approach made by Buttler et al. [2016] was to analyze the load and its relation to wind and solar energy.</td>
<td>Wind - Solar PV - Load</td>
<td>Europe</td>
</tr>
</tbody>
</table>
03. Methodology

3.1. Data Processing of the wind and solar PV potential power generation database for representative locations of Latin America

This study analyzes the potential integration between renewable energy sources in LA and helps to understand how complementarity can smooth out the resource variability.

The flowchart below shows the steps taken to achieve the goal of the study. The assumptions and procedures of each step are described hereafter.
Fig. 4. Flowchart of the steps taken to achieve the goal of the study

a) IDF Database

The Inter-American Development Bank (IDB) provided a database of fifteen years of wind speed and solar irradiation profiles for LA under an hourly scale, as well as the potential power generation from these resources. The resource data is a byproduct of the IDB’s Grid of the Future study that looked into an optimal long term integration of solar and wind energy in Latin America’s energy matrix.

The fifteen years (2000-2015) of hourly values for each area’s capacity factor were computed by simulated historical meteorological data with the Weather Research and Forecasting (WRF) model, which was run at a 27-km resolution.

This study considered the potential power generation data series instead of the series of wind speed and solar irradiance, since renewable energy integration is the prime goal.

The potential was estimated based on a gross capacity potential for solar and wind energy for determined areas that were considered according to some land use criteria that tries to limit the capacity to a realistic upper threshold.

The potential of solar generation for each area was computed by a constant energy density of 29.77 MW/km² (representative for a single-axis PV tracking system) and a minimum global horizontal irradiance (GHI) threshold of 171W/m² (in order to be considered economically feasible).

For the wind resource, this study re-evaluated the potential power generation based on a 3.3 MW turbine at 100m hub height, with a cut in/out speeds of 3.5 m/s and 25 m/s, respectively, a rated speed of 15 m/s, a rotor radius of 112 m (r), a maximum Cp of 0.45 and an efficiency of 95% (η). Other values considered were an air density of 1.225kg/m³ and the wind speed (v).

The power curve is shown in (Eq. 5) [Bieniawski et al., 2007]

\[ P_{\text{power}} = \frac{1}{2} \rho A C_{\text{p}} v^3 \]  

(Eq. 5)

b) Database Treatment

This study analyzed 50 hotspots for wind energy and 46 hotspots for PV solar energy. The power generation data for each hotspot in the hour h were built by the sum of the multiplication of the potential power generation in the hour h by the gross installed capacity. Both terms of the equation consider the respective area and capacity factors (CF).

According to the equation (Eq. 6)

\[ P_{\text{Power Generation Hotspot}} = \sum P_{\text{CF}} \]  

(Eq. 6)

Where \( P_{\text{Power Generation}} \) is the potential power generation (in the hour h) for a specified area and capacity factor and \( C_{\text{F}} \) is the gross installed capacity for each area and CF.

Hence, a unique capacity potential and generation profile were built for each area.

c) Database Processing

This study used two software packages to analyze the wind and solar data: RStudio and Microsoft Excel.

The first analysis aimed to calculate the monthly (\( G_{\text{monthly}} \)) and yearly (\( G_{\text{year}} \)) generation values for each region, as (Eq. 7) and (Eq. 8), respectively.

\[ G_{\text{monthly}} = \frac{1}{m} \sum_{m=1}^{M} G_{\text{h,m,y,a}} \]  

(Eq. 7)

\[ G_{\text{year}} = \frac{1}{y} \sum_{y=1}^{Y} G_{\text{h,y,a}} \]  

(Eq. 8)

In order to understand the variability behavior of the hotspots, the following variability indices were calculated: Inter-Hourly Variability (IHV), Inter-Monthly Variability (IMV) and Inter-Annual Variability (IAV).

The long-term index and the hourly ramping rates were also determined; for the ramping rates, this study built the histogram curve to evaluate the frequency distribution of this index for each area.

The potential complementarity between areas and resources was evaluated by linear correlation method, Pearson method. Regions that present negative correlation are defined as candidate regions for integration, because the negative correlation leads to a variability smoothing effect in the final energy output. This allows identifying the complementarity between the resources to reduce the intermittency of energy production [Kougias et al, 2016].

The correlation value was calculated for each year of the series (15 years) on hourly and monthly basis. The result is fifteen arrays correlations (86 x 86).

d) Decision Criteria

This study defined two decision criteria to determine areas with potential complementarity considering the computed correlations: i) if the frequency of negative correlation is equal or higher than 12 years, in other words equal or higher than 85% of the cases. This condition aims to guarantee the existence of a consistent correlation between the areas and ii) if the intensity of area-resource correlation is higher than the median of all correlations, then the area-resource is considered as a good candidate to complementarity.

The percentage difference between the generation in the hour h and m is expressed as:

\[ \% = \frac{|P_{h} - P_{m}|}{P_{h}} \times 100 \]  

(Eq. 9)

Where

\( a = \) the considered hour

\( J = \) the year of analysis

\( m = \) the month to be analyzed

\( a = \) the area of the database to be analyzed

\( \gamma = \) is the number of hours in the month

\( \gamma = \) is the number of hours in a year

For the five areas that presented the strongest negative correlation coefficient.

With the intention of giving the reader an idea of how the best correlations are geographically distributed, this study also created some maps to represent the best complementarity regions. Hence, fourteen maps were created: two showing hourly correlation for wind and solar power generation, nine for monthly correlation of wind and solar power, and three for monthly correlation considering the standard year for hydro-solar wind generation, to be explained in the next section.

3.2. Selection and data gathering of representative hydrological basins of representative locations

Unlike wind and solar data that were provided by the Inter-American Development Bank (IDB), the information of hydropower was acquired from the electric power sector of the countries studied in this report. This can cause some inconsistencies in the analysis of complementarities with other sources or even in the typical year trajectory of the hydropower hotspots.

The analysis of hydraulic sources sought to form clusters of hydraulic energy resources for a same country according to its hydrological patterns in order to form hotspots. These were used as parameters to determine the complementarity to wind and solar hotspots.

The methodological procedure consisted firstly in creating a database composed of a time series of natural monthly streamflow of rivers where hydroelectric plants are located and monthly electricity generation data of hydropower. These data were obtained mainly from government regulatory bodies and power generating companies.

All monthly data of natural streamflow were normalized to zero mean and standard deviation equal to one and subsequently a standard year for each hydroelectric plant was shaped based on the monthly average of the normalized data.

The standard years of all hydroelectric plants that belong to the same country were plotted and grouped according to their hydrological patterns. In doing so, hydroelectric plants that exhibit similar behavior throughout the year could be clustered to create a hotspot.

The standard year of hotspots were designed by summing streamflow data of hydroelectric power plants previously
grouped as mentioned above. Next, this sum was normalized and a monthly average calculated, yielding a standard year that represents the typical hydrological behavior of a basin or a group of basins in a specific country.

In the case of binational hydroelectric plants, in each nation the value of the flow was reduced by half to avoid double counting, as in the case of Itaipú (Brazil and Paraguay), Yacyretá (Argentina and Paraguay) and Salto Grande (Argentina and Uruguay).

For countries in which only electricity generation was available and no additional information was found, the same procedure of normalization, aggregation and establishment of a standard year was done. However, a supplementary investigation was held with the purpose of removing unproductive plants data. This analysis was accomplished by plotting the standard year of hydroelectric power plants. Those that showed a pattern of homogeneous generation over the months were considered unproductive plants and thus withdrawn from the database.

This step is necessary due to unproductive hydroelectric plants that can generate energy in drier periods, which may distort the analysis of the natural hydrological pattern of the month the plant is located and consequently misrepresent the typical year of the hotspot.

For Guyana, Mexico, Panama, Suriname and Venezuela neither streamflow nor electricity generation data were found. For this reason, these countries were not included in the hydrocomplementarity analysis. For Argentina, Chile and Ecuador, mean streamflow data was found for some rivers but without their gauge locations. Thus, in the absence of more accurate data, this study considered that these data represent the streamflow where the hydroelectric plants are located.

In Brazil, hydroelectric plants were grouped by basins. The data used was the natural monthly inflow of the hydroelectric plants in the period between 1991 and 2014 provided by the Operador Nacional do Sistema Elétrico (ONSa). In this case of cascade hydroelectric plants, this study considered only the plant or the group of plants with the highest flow. Therefore, the flow of the plants downstream was added to the flow of plants located in other rivers of the same basin. The standard year basins which achieved the same seasonality in the typical year were grouped at the same hotspot, so there were three hotspots. The Brazil 1 hotspot consists of the South Atlantic and Uruguay basins, while Brazil 2 is formed by the Eust and Southeast regions. Finally, Brazil 3 is composed of the Parnaíba, São Francisco, Tocantins, Amazonas, Paraguay and Parana basins. Brazil 1 has an upward trend from May to October. On the other hand, Brazil 2 has an increase in flow from October until the end of the year. Brazil 3 has higher flow rates between the months of October and March (ONSb).

Brazil was the most complex case, because it has more hydroelectric plants and a bigger territory than other Latin American countries.

There is no data for many months of the six plants in French Guiana which are addressed in this study. The French Guiana hotspot was obtained by natural flow data of the hydroelectric power plants between the period 2010 and 2016, which were provided by the Système d’Information du Développement Durable et de l’Environnement (SIDE). The flow rates of French Guiana have similar behavior throughout the year so they were allocated in the same hotspot.

Data gathered for Paraguay was the inflow to its two major binational hydroelectric power plants: Itaipu and Yacyretá. The natural flow data from Yacyretá was attained at the official website of the hydroelectric plant Entidad Binacional Yacyretá (EYB) while the Itaipu information was obtained at Operador Nacional do Sistema Elétrico (ONS). As these plants show similar trajectories, they were located at the same hotspot.

In Uruguay, the typical year was based on monthly electricity generation data provided by the Administración de Desarrollo del Mercado Eléctrico (ADME) from 2012 to 2016. After normalization, it was observed that the Uruguayan hydroelectric power plants had a similar trend during the year and for this reason this country has only one hotspot.

In Argentina, the standard year was obtained from streamflow data between 1994 and 2016 from the Compañía Administradora del Mercado Mayorista Eléctrico (CAMMESA). In this study seven hydroelectric plants were analyzed and properly allocated in two hotspots. One formed by six plants and the other by the Yacyretá plant, because they have different hydrological behaviors. In the first one, the flow rates start low and increase until the middle of the year, in Argentina 2 the opposite happens, with the flow falling up to September (CAMMESA).

In the same direction, Chile was also divided into two hotspots. To create the standard year, the streamflow data between 2000 and 2016 was used by the Sistema Nacional de Información del Agua (SNIA). Chile 1 comprised the Biobío and Maule regions, while the Metropolitan and O’Higgins regions were part of hotspot Chile 2. Chile 1 has an upward flow trend from January to July and falls between this month and December. On the other hand, Chile 2 shows a fall from January to July and there is an increase in the flow from that time, lasting until the end of the year (SNIA).

In the Bolivia analysis, the data provided by the Comité Nacional de Despacho de Carga (CNDCE) was the natural monthly inflow, in the period between 2006 and 2016. The Corani and Choqueyrahu are the largest hydropower plants and the others are very small. The principal hydroelectric plants are together in just one hotspot. All of them showed an increase in flow up to March and then a decline until September, when their flows increase again at the beginning of the rainy season (CNDCE).

In Ecuador, the standard year was obtained from streamflow data between 1990 and 2013. In this country, two distinct hydrological patterns were identified. The Ocuca, Marcel Laniado and Manta hydroelectric plants formed the first hotspot which had a higher flow rate between January and June. The second hotspot was defined based on data from the Paute and Mazar hydroelectric plants that had higher flow rates between May and September (INAHUH). Colombia’s typical year was obtained through natural streamflow data between the period 2000 and 2014, published by the Interconexion Eléctrica S.A (ISA). This country has two hotspots. Colombia 1 includes the regions of Antioquia, Caribbean and East, while Colombia 2 is composed by Valle and Central areas. The first one has an increase in flow from January to July and then drops to the end of the year. However, the second region shows a really different trajectory, with flow increasing until May, then falling sharply until September and growing again from this month until December (ISA).

In Costa Rica, the standard year represents monthly electricity generation data provided by the Instituto Costarricense de Electricidad (ICE) from 2011 to 2013 [ICE]. These data were separated into three distinct patterns that underpinned the three hotspots analyzed in this report. The first hotspot shows a pattern of higher electricity generation between the months of January and July, represented by the Dengo, Arenal and Sandíal hydroelectric plants. The second hotspot is represented by large plants of Garita 1, Garita 2, Garita 3 and 4, Pito and Poas I and II hydroelectric plants, which have higher electricity generation between the months of September and December. The third hotspot was represented by Peñas Blancas, Cariblanco, Tapanti, Arenal, Zarcero and Don Pedro hydroelectric plants that have a higher generation in July, November and December.

In El Salvador, the standard year was based on monthly inflow data between the period 2005 to 2014 of Guayabo, Cerrón Grande hydropower plants on 5th November and 15th September, which were provided by the Superintendencia General de Electricidad y Telecomunicación (SIGET). The standard year obtained shows higher flow rates between the months of July to November (SIGET).
04.

Results

This section presents the most relevant results, as well as being a tutorial to understand all the products obtained throughout the study.

4.1. Energy Complementarities – Temporal analysis

Figure 5 and Figure 6 show the potential generation and possible complementarity between two areas that are strongly correlated on an hourly basis (WIND_BR_A06 and SOLAR_CL_A06). The figures show that the Brazilian site has intense wind activity in the early hours of the day and the solar resources of the other area could complement its reduction during the day. It also shows the availability of resources throughout typical summer and winter weeks exhibiting seasonal impacts. Because the installable solar capacity is so much greater in Chile than in Brazil the potential generation that would promote complementarity was normalized, utilizing the P50 criteria for the firm wind capacity. It means that this analysis assumes that the solar capacity is equal to the median of the wind generation time series in the Brazilian site.

7 Original criteria indicated by the Brazilian Ministry of Mines and Energy (Ministério de Minas e Energia) to calculate the amount of energy expected to be produced by a wind power plant as a way to mitigate the economic risk associated with inter-annual resource variability. It means that there is a 50% likelihood that the farm’s output will be greater than the firm energy determined by this criteria.
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Figure 5. Variability of two areas with strong hourly correlations during a summer week.

Figure 6. Variability of two areas with strong hourly correlations during a winter week.

The twenty pairs with the strongest hourly correlation are listed in Table 3. It is clear that all those strongest correlations are between the area WIND_BR_A06 and other solar resource hotspots spread over the region. This occurs due to the fact that the area in Brazil has greater wind speeds during the night and can be complemented by solar generation during the day.

Figure 7 and Figure 8 show the seasonal complementarity between the areas of WIND_PE_A01 & WIND_PA_A01 and WIND_BR_A01 & WIND_BR_A03 respectively. These areas have a high (absolute) value of correlation coefficient on a monthly potential energy generation basis. Once again, the monthly totals were adjusted so that the amounts of energy generation could complement each other resources despite the different potential between those areas. The twenty pairs with strongest monthly correlation are listed in Table 4.

Table 3. Twenty pairs with the highest hourly correlation factors

Table 4. Twenty pairs with the strongest monthly correlation factors

Figure 7. Seasonal complementarity between areas with a high monthly correlation factor: WIND_PE_A01 and WIND_PA_A01
4.2. Energy Complementarities – Geographic analysis based on an hourly scale data

Maps were implemented to specify the regions with good evidence of complementarity of wind and solar resources in Latin America, using the hourly data resources. These maps were developed using the decision criteria, frequency and intensity of correlations, enabling the visualization of areas with good potential for complementarity between energy resources.

It is worth noting that the assessed areas consider just the potential power resources integration. The physical capacity through electric interconnections was not evaluated in order to integrate these areas. This would require a different type of analysis, including the different modes of physical and economic integration between regions in Latin America.

Figure 9 shows the correlation of WIND_BR_A06 hotspot with WIND_VE_A03 hotspots. The correlation is -0.40, indicating a good complementarity between regions. All correlations are higher than -0.40, indicating a good complementarity between regions. That is, the wind regime between these regions is reverse during the day. A reason to WIND_BR_A06 hotspot to be correlated with all these solar sites is the typical wind that blows in this area during the night. This negative correlation can be used to minimize the total variability of the resources.

The frequency of negative correlations and intensity of these correlations were used as decision criteria. The results presented in Figure 9 and Figure 10 show negative correlation over the 15 years of the time series. Thus, the major decision criteria become the value of the correlation intensity between the areas and resources.
4.3. Energy Complementarities – Geographic analysis based on a seasonally approach

Maps\textsuperscript{10} were implemented to specify regions with good evidence of complementarity of wind and solar resources in Latin America, using the average monthly availability of resources. These maps were developed using the decision criteria\textsuperscript{11}, frequency and intensity of correlations, enabling the visualization of areas with good potential for complementarity between energy resources.

Figure 11 shows the correlation of WIND_BR_A03 hotspot with WIND_VE_A04, WIND_VE_A03, WIND_VE_A02, WIND_SU_A01 hotspots. All correlations are greater than -0.81, which indicates a very good complementarity between regions. That is, the wind regime between these regions is reversed during the year. This negative correlation can be used to minimize the total variability of the resources.

Figure 12 shows the correlation of WIND_BR_A04 hotspot with WIND_VE_A04, WIND_VE_A03, WIND_VE_A02, WIND_SU_A01 hotspots. All correlations are greater than -0.81, which indicates a very good complementarity between regions. That is, the wind regime between these regions is reversed during the year. This negative correlation can be used to minimize the total variability of the resources.

Figure 13 shows the correlation of WIND_BR_A05 hotspot with WIND_VE_A03 hotspots. The correlation is -0.88, which indicates a very good complementarity between regions.

Figure 14 shows the correlation of WIND_BR_A01 hotspot with WIND_BR_A05, SOLAR_BR_A03, WIND_PE_A01 hotspots. The correlation is -0.80, which indicates a very good complementarity between regions.

Figure 15 shows the correlation of WIND_AR_A01 hotspot with SOLAR_ES_A01, SOLAR_PA_A01, WIND_BR_A01 hotspots. All correlations are greater than -0.80, which indicates a very good complementarity between regions.

Figure 16 shows the correlation of WIND_EC_A01 hotspot with SOLAR_VE_A03 hotspots. The correlation is -0.82, which indicates a very good complementarity between regions.

Figure 17 shows the correlation of WIND_CL_A01 hotspot with SOLAR_MX_A01 hotspots. The correlation is -0.84, which indicates a very good complementarity between regions.

\textsuperscript{10} These maps were drawn based on arrays of monthly averages of the correlations of time series of wind and solar resources. Only 20 regions with best indicative of complementary are mapped in the main text.

\textsuperscript{11} The frequency of negative correlations and intensity of these correlations were used as decision criteria. The results presented in the maps of this section show negative correlation over the 15 years of the time series. Thus, the discussion focuses on the value of the correlation intensity between the areas and resources in the text.
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Figure 13. Region WIND_BR_A05 and its related regions with good evidence of monthly complementarity

Figure 14. Region WIND_BR_A01 and its related regions with good evidence of monthly complementarity

Figure 15. Region WIND_AR_A01 and its related regions with good evidence of monthly complementarity

Figure 16. ZAP EÓLICA_CL_A01 y sus regiones relacionadas con buenas evidencias de complementariedad
4.4. Energy Complementarities – Geographic analysis based on a seasonal approach with hotspots for hydro power generation

Maps were implemented to specify the regions with good evidence of complementarity of wind, solar and hydro resources in Latin America, using the average annual profile of the resources to estimate the correlation. These maps were developed using just the intensity decision criteria, as the frequency criteria is not available for this analysis. All years were clustered into an average standard year. The intensity of correlations enables the visualization of areas with good potential for complementarity between those energy resources.

Figure 20 shows the correlation of Hydro_Brazil hotspot with Hydro_Argentina, Hydro_Chile, Hydro_Guatemala, Wind_AR_A03, Wind_BR_A03, Wind_BR_A10 and Wind_PE_A03. All correlations are more negative than -0.9, which indicates an excellent complementarity between regions. The correlation is -0.9, which indicates an excellent complementarity between regions.

Figure 21 shows the correlation of Hydro_Paraguay hotspot with Wind_AR_A01, Wind_BO_A01, Wind_BR_A05, Wind_BR_A10, Wind_PE_A01, Wind_PE_A02 and Wind_PE_A03. All correlations are greater than -0.9, which indicates an excellent complementarity between regions. The correlation is -0.9, which indicates an excellent complementarity between regions.

Figure 22 shows the correlation of Hydro_Chile with Hydro_Brazil, Hydro_Peru, Solar_PA_A01, Wind_BR_A01, Wind_CO_A02, Wind_SU_A01 and Wind_VE_A03. The correlation is -0.9, which indicates an excellent complementarity between regions.

\* These maps were drawn based on arrays of average annual profile of the correlations of time series of wind, solar and hydro resources. It was necessary to build a typical year to handle the problem of different lengths of time series between resources and regions. Only 10 regions with the best complementarity values are mentioned in the main text.
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Results

SECTION I

4.5. Summary of Results

The available data were treated to provide variability indices and correlations between the assessed hotspot regions. This report focuses on the major results. Figure 23 and Figure 26 show the IAV intensity for each wind and solar hotspot, respectively.
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Section I

Figure 25. IAV intensity for wind hotspots

Figure 26. IAV intensity for solar hotspots
05. Discussion

The present report aimed to analyze the variability and complementarity between renewable energy resources in Latin America. The resources addressed in this analysis are wind, solar, and hydropower. The main result of this work is the information generated through the statistical analysis of the wind, solar, and hydro databases in Latin America. The analysis focuses on understanding the seasonality of the resources, their variability, and possible complementarity.

To reach this objective, several steps were taken. A review of the state of the art for variability indices and studies addressing complementarities between renewable sources was performed. At the same time, the hourly resource data of solar irradiation and wind speed were transformed into electrical energy. With this approach, it was possible to evaluate the data in the expected level of this research: energy integration.

Natural cycles in the context of solar energy have three dimensions: seasonal variation, daily variations (from dawn to dusk) and short-term fluctuations due to weather conditions. Wind power, on the other hand, can fluctuate at various time scales: it is subject to seasonal variations of peak electricity production in winter or summer depending on the region, as well as diurnal and hourly changes. There are also very short-term fluctuations in the intra-minute and inter-minute timeframe, that according to IEA (2005) are small relative to installed capacity, compared to hourly or daily variations. Furthermore, wind patterns can also be affected by orography since it plays an important role in the screening, deflection, and acceleration of the wind and can create turbulence. This study calculated variability indices using a database with an hourly scale. The calculated indices showed a larger variability for wind power than for solar power generation. This can be explained as in solar power (different to the wind power case) the major variations occur in an intra-minute and inter-minute timeframe and by the larger sensitiveness of wind power to its natural resource (wind speed). Indeed, the wind generation relates to the wind speed through a cubic function, while solar generation presents an almost linear relationship with solar irradiance. An important fact to remark is how strong the region WIND_BR_06 is correlated with other areas: the ten strongest correlations found were from this cited area, this is because this hotspot presents trends of high wind speeds at night; therefore, it is well correlated with many solar areas.

In addition, when the monthly correlation was analysed, for correlations for all data series (done for wind and solar power) and for the correlation of typical years (including hydropower in the correlation analysis), Brazil plays an important role regarding renewable energy integration in LA, since it presents the strongest capacity to complement and being complemented by several LA countries. Besides Brazil, Venezuela also presents strong correlations with countries like Paraguay, Brazil and Ecuador, mainly under a seasonal pattern.

By evaluating the potential availability of resources and complementarity in hotspots in Latin America, it is possible to conclude that energy integration in Latin American countries is a suitable strategy to deal with variable renewable sources electricity generation. Therefore, policymakers and energy planners should work to find ways to dismantle some of the barriers - such as regulatory and interconnection issues - for developing this potential.
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06 — References


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SECTION II

Assessment of Climate Change Impacts on Solar and Wind Energy Resources in Latin America
Contribution of variable renewable energy to increase energy security in Latin America

SECTION II

Background

Introduction

Scientific evidence of possible changes in climate has been raising interest in the public and the scientific community [IPCC, 2013]. According to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change (AR5), CO2 emissions have increased by 40% since the pre-industrial period, mainly due to fossil fuel emissions followed by changes in land use [IPCC, 2013]. According to that report, the future climate will begin to behave less like past climates in the coming decades. A modification on climate would affect society and the economic system through multiple sectors, such as altering agricultural yields, influencing coastal areas or changing energy production and consumption. The energy system may be one of the parts of the economy most affected by climate change [Ciscar et al., 2014]. Considering the fact that energy is indispensable to many other sectors, all the climate impacts in the energy sector would be reflected extensively throughout the rest of the economy.

Climate change may affect renewable sources more intensively than the fossil ones since renewable energy endowments are related to a flux of energy, which is intimately related to climate conditions. Fossil fuels can be stocked, so climate change would impact only the access to these resources [Schaeffer et al., 2012, Burnett et al., 2014].

However, implications of possible changes in the potential of renewable resources, such as wind and solar, must be properly understood for future planning purposes. Wind speed and cloudiness (variable that affects solar resource) are strongly influenced by local temperature gradients [Fant et al., 2016].

To plan and operate energy systems, it is very common to use a variety of models, in order to evaluate the effects of climate on operation and planning. However, conventional energy analysis assumes that climate variables are constant, with no modification in time, but this premise may actually increase uncertainty in decisions in a climate change framework [Schaeffer et al., 2012]. So, for the development of policies that aim to cope with climate change, estimating the susceptibility of energy systems and incorporating them into long-term energy planning and operation is imperative in order to improve the reliability of the projects.

In this way, experts from different economic sectors use climate projections as a basis for determining possible impacts and developing mitigation and adaptation actions. Modeled projections of changes in the long-term future state are attractive for national energy investments that are considering large penetration of renewable energy generation in their portfolios [Fant et al., 2016].

This study aims to determine the possible impacts on future long-term wind and solar energy resource complementarity due to climate change for selected regions in Latin America (LA). To do this, results from General Circulations Models (GCM) and a Representative Concentration Pathway (RCP) of the IPCC’s fifth Assessment Report (AR5) will be used. A downscale exercise will be performed in order to obtain data at the geographical resolution of the selected regions. The variables obtained from the GCMs will be linked to the wind and solar resources of the data base supplied by the Inter-American Development Bank (IDB) to assess the impact of climate change in the complementarity evaluation carried out in Section I.
Climate change impact assessments are commonly made with the use of General Circulation Models (GCM). These models are three dimensional representations of the atmosphere and its interactions with land surface and oceans [IPCC,2013]. They are used to project future climate under different forcings, including those related to concentrations of GHG. Therefore, they project climate based on different trajectories for GHG emissions and, as a result, radiative forcings. Such trajectories are represented by a range of scenarios, among which the Representative Concentration Pathways (RCP) [Moss et al, 2010] are the most recent ones. The sections below describe the choice of RCP and GCM used in this study to project the impacts of climate change on the complementarity of renewable energy sources in Latin America.
2.1. Review of the Global Circulation Models (GCMs)

General Circulation Models are the primary tools available for investigating the response of the climate system to various forcings, for making climate predictions on seasonal to decadal time scales and for making projections of future climate over the coming century and beyond [Flato, 2013]. This section draws on GCM features and specifically on the Hadley Centre Global Environment Model (HadGEM2) and the Model for Interdisciplinary Research on Climate (MIROC5), as these constitute a set of coordinated and thus consistent and increasingly well-documented climate model experiments.

A GCM is composed of many grid cells that represent horizontal and vertical areas on the Earth’s surface (Figure 1) in each one of the cells, GCMs compute the following: water vapor and cloud atmospheric interactions, direct and indirect effects of aerosols on radiation and precipitation, changes in snow cover and sea ice, the storage of heat in soils and oceans, surface fluxes of heat and moisture, and large-scale transport of heat and water by the atmosphere and oceans [Wilby et al., 2009].

The spatial resolution of GCMs is generally quite coarse, with a grid size of about 100–500 kilometers. Each modeled grid cell is homogenous, i.e., within the cell there is one value for a given variable. Moreover, they are usually dependable at timescales of monthly averages and longer. In summary, GCMs provide quantitative estimates of future climate change that are valid at the global and continental scale and over long periods [ARCC, 2014].

Atmosphere–Ocean General Circulation Models (AOGCMs) were the “standard” climate models assessed in the AR4 and AR5. Their primary function is to understand the dynamics of the physical components of the climate system (atmosphere, ocean, land and sea ice), and to make projections based on future greenhouse gas (GHG) and aerosol forcing. These models continue to be extensively used, and in particular are run (sometimes at higher resolution) for seasonal to decadal climate prediction applications in which biogeochemical feedbacks are not critical. In addition, high-resolution or variable-resolution AOGCMs are often used in process studies or applications with a focus on a particular region [ARCC, 2014]. An overview of the AOGCMs can be found in Table 1.
Earth System Models (ESMs) are the current state-of-the-art models, and they expand on AOGCMs to include representation of various biogeochemical cycles such as those involved in the carbon cycle, the sulfur cycle, or ozone [Flato, 2013]. These models provide the most comprehensive tools available for simulating past and future responses of the climate system to external forcing, in which biogeochemical feedbacks play an important role. An overview of the ESMs can be found in Table 1.

It is crucial therefore to evaluate the performance of these models, both individually and collectively. In particular, the IPCC (2014) draws heavily on model results collected as part of the Coupled Model Intercomparison Projects (CMIP5 and CMIP6) [Meethal et al., 2007; Taylor et al., 2012].

In Table 2 a few CMIP model names are used. HT stands for High-Troposphere, which has a full resolved stratosphere with a model top above the stratosphere. AMIP stands for models with atmosphere and land only, using observed sea surface temperature and sea ice extent. A component is colored when it includes at least a physically based prognostic equation and at least a two-way coupling with another component, albeit implicitly. For aerosols, lighter shading means ‘semi-interactive’ and darker shading means ‘fully interactive’. The resolution of the land surface usually follows that of the atmosphere, and the resolution of the sea ice follows that of the ocean. In moving from CMIP5 to CMIP6, note the increased complexity and resolution as well as the absence of artificial flux correction (FC) used in some CMIP5.

2.1.2. MIROC

MIROC is a Japanese cooperatively developed model known as Model for Interdisciplinary Research on Climate (MIROC), version 5 (Watanabe et al., 2010). It is spectral in the atmospheric component with resolution T85, which is approximately 150 km in the horizontal, and has 40 vertical atmospheric levels. It is coupled to COCO-4.5 ocean model (Hasumi, 2007) with 50 levels in depth and T63 resolution in the horizontal. The ocean model, the SPRINTARS, is coupled to cloud microphysical processes and the radiation scheme, it uses the MATHIS ocean surface scheme [Takata, Emori and Watanabe, 2005] with 6 soil layers. Each grid box is formed by three tiles of sea ice. The land model solves stratosphere with a model top above the stratosphere, and at least a two-way coupling with another component, albeit implicitly. For aerosols, lighter shading means ‘semi-interactive’ and darker shading means ‘fully interactive’. The resolution of the land surface usually follows that of the atmosphere, and the resolution of the sea ice follows that of the ocean. In moving from CMIP5 to CMIP6, note the increased complexity and resolution as well as the absence of artificial flux correction (FC) used in some CMIP5.

2.2. The Representative Concentration Pathways (RCP)

Climate change generates effects or influences certain processes and natural phenomena. As the characteristics of each environment are constantly changing over time, the assessment of an impact must presuppose an analysis of these conditions at a future time. For this, climate models are applied using the information of future scenarios. An RCP is a time-dependent pattern of greenhouse gas emissions, concentrations and accompanying land use and land cover scenarios for the time period up to 2100, and extensions have been formulated for the centuries thereafter.

The scenarios selected from the literature were published during the 2006–2007 period. As new historical data become available and modeling methods are improved, each team is encouraged to update their original scenario and expand their results, without changing the basic assumptions behind them [van Vuuren et al., 2011].

The RCPs are intended to form a key element of the new process. They were selected to span the range for those factors that determine future climate change [van Vuuren et al., 2011]. In total, four RCPs were developed: RCP2.6, RCP4.5, RCP6 and RCP8.5, with the associated numbers indicating the radiative forcing reached in [W/m²] at the end of the 21st century compared to the pre-industrial state [Wild et al., 2015]. Each of the RCPs covers the 1850–2100 period, and extensions have been formulated for the period thereafter (up to 2500) [van Vuuren et al., 2011].

As part of this process and based on discussions within the context of the IPCC, several design criteria were established [Moss et al. 2008]. These criteria stem from their intended use to facilitate climate research and assessment: 1) The RCPs should be based on scenarios published in the existing literature, developed independently by different modeling groups and representative of the entire literature, in terms of emissions and concentrations; 2) The RCPs should provide information on all components of radiative forcing that are needed to assess the impact of climate change; 3) The RCPs should cover the time period up to 2100, but information also needs to be made available for the centuries thereafter.

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Overview of representative concentration pathways (RCPs)

Table 2. Overview of representative concentration pathways (RCPs)

| RCP 8.5 | Rising radiative forcing pathway leading to 8.5 W/m² (~1970 ppm CO2) by 2100 |
| RCP 6 | Stabilization without overshoot pathway to 6 W/m² (~850 ppm CO2) at stabilization after 2000 |
| RCP 4.5 | Stabilization without overshoot pathway to 4.5 W/m² (~650 ppm CO2) at stabilization after 2000 |
| RCP 2.6 | Peak in radiative forcing at ~3 W/m² (~500 ppm CO2) before 2000 and then decline (the selected pathway declines to 2.6 W/m² by 2090) |

Approximate radiative forcing levels were defined as ∆/γ of the state-level in W/m² relative to pre-industrial levels. Radiative forcing values include the net effect of all anthropogenic GHGs and other forcing agents.

Table 3. Main characteristics of each RCP

<table>
<thead>
<tr>
<th>Scenario Component</th>
<th>RCP 2.6</th>
<th>RCP 4.5</th>
<th>RCP 6</th>
<th>RCP 8.5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Green house gas emissions</td>
<td>Very low</td>
<td>Medium-low mitigation and very low baseline</td>
<td>Medium-base line and high mitigation</td>
<td>High baseline</td>
</tr>
<tr>
<td>Agricultural area</td>
<td>Medium for cropland and pasture</td>
<td>Very low for both cropland and pasture</td>
<td>Medium for cropland but very low for pasture (total low)</td>
<td>Medium for both cropland and pasture</td>
</tr>
<tr>
<td>Air pollution</td>
<td>Medium-low</td>
<td>Medium</td>
<td>Medium</td>
<td>Medium-high</td>
</tr>
</tbody>
</table>

The elaborate development process to create a RCP is necessary so that the RCPs may provide a consistent analytical thread that runs across communities involved in climate research. RCPs are reasonable with their design criteria. Given their comprehensiveness in terms of sources covered, as well as in spatial detail, they provide a unique basis for detailed climate model runs. The assessment of vulnerability, impacts and adaptation requires not only a description of expected climate change, but also associated a description of socioeconomic conditions [van Vuuren et al., 2012]. The RCPs represent an important step in the development of new scenarios for climate research and provide a good basis for exploring the range of climate outcomes by the climate modeling community [van Vuuren et al., 2011].

2.3. Impacts of Global Climate Change on Renewable Resources in LA

Several energy sector studies are based on climate models (General Circulation Models – GCMs) in order to establish these possible weather variations may have a direct or indirect impact on energy supply and demand. According to Luena [2010], the impacts of climate change on several sectors have been studied since the 1990s, however, literature on the effects on the energy sector, particularly electricity is relatively new and limited. In this section, a scientific literature review is done on climate change impacts, taking into consideration more renewable sources, especially it focuses more on wind.

In Central and South America, temperatures have risen by 0.7°C and 1°C since the mid-1970s, except for coastal Chile, where they have fallen by 1°C, and annual precipitation have risen in the southeastern part of South America and fallen in Central America and the southern and central parts of Chile. The region has experienced changes in climate variability and significant impacts from extreme climate events, although many of these extreme phenomena are not necessarily attributable to climate change [Maggini et al., 2014; IPCC, 2014].

The Latin American and Caribbean region is also affected by various climate phenomena including the Intertropical Convergence Zone, the North and South American monsoon system, El Niño Southern Oscillation, Atlantic Ocean oscillations and tropical cyclones, [IPCC, 2014]. These phenomena affect the sub-regional climate and changes in their patterns have major implications for climate projections. The El Niño Southern Oscillation will continue to be (at a high confidence interval) the dominant form of interannual variability in the tropical Pacific, and rising humidity levels will likely intensify El Niño precipitation variability [IPCC, 2014].

3.1. Impacts of Global Climate Change on Wind Resource

Renewable generation capacity in Latin America and the Caribbean, at the end of 2015, amounted to 212.4 GW. According to IRENA [2015] wind energy accounted for 7% share of the regional total, with an installed capacity of 15.5 GW. Renewable energy generation capacity increased by 13.1 GW during 2015, the largest annual increase since the beginning of the time series (year 2000). Wind capacity increased by 4.6 GW [IRENA, 2016].

Expansion of wind energy installed capacity is poised to play a key role in climate change mitigation. However, wind energy is also susceptible to global climate change. Some changes associated with climate evolution will likely benefit the wind energy industry while other changes may negatively impact wind energy developments, those ‘gains and losses’ are dependent upon the region under consideration. Herein we review possible mechanisms by which global climate variability and change may influence the wind energy resource and operating conditions [Pryor and Barthelmie, 2013].

Wind energy, like many of the renewable technologies, is susceptible to climate change, because the ‘fuel’ is related to the global energy balance and resulting atmospheric motion (Hubbert, 2009). Hence here we seek to close the loop by asking the question: what impact might global climate change have on the wind energy industry?

Atmospheric conditions enter into the design and operation of wind turbines and wind farms largely under the rubric of ‘external conditions’. The wind climate governs the energy density in the wind and hence the power that can potentially be harnessed:

\[ E = \frac{1}{2} \rho U^3 \]  

(Eq. 1)

In this equation, \( E \) represents the energy density (Wm²), \( \rho \) is the air density (Kg m⁻³) and \( U \) the wind speed at hub-height (m s⁻¹).

Given the energy in the wind is the cube of wind speed (Eq. (1)), a small change in the wind climate can have substantial consequences for the wind energy resource. For a change in wind speed at turbine hub-height of 0.5 m s⁻¹ from 10 to 10.5 m s⁻¹ (i.e. a 10% change), the energy density increases by over 30%. It is also clear that the wind resource is largely dictated by the upper percentiles of the wind speed distribution, a factor that is further amplified by the non-linear relationship between incident wind speed and power production from a wind turbine [Pryor and Barthelmie, 2013].

The wind climate also governs aspects of the wind turbine design, via its governing role in wind turbine loading through, for example, turbulence intensity, wind shear across the turbine blades, and transient wind conditions such as the occurrence of extreme wind speeds and directional changes [DNV/RISO, 2002]. Other atmospheric conditions that are of importance to the design, operation or power production from wind turbines include operational temperatures, air density, icing and corrosion and abrasion due to airborne particles [DNV/RISO, 2002].

The principal and most direct mechanism by which global climate change may impact the wind energy industry is by changing the geographic distribution and/or the inter- and intraannual variability of the wind resource. Research undertaken to quantify this effect generally relies on application of downscaling methodologies designed to extract higher resolution projections of climate parameters of interest from coupled Atmosphere-Ocean General Circulation Models [Pryor and Barthelmie, 2013].

The inter- (and intra) annual variability of wind speeds, wind indices and energy density are naturally a function of the regional climate, and frequency of storm systems, and the spatial scale of aggregation. At short time scales this variability leads to variable output of electricity production [European Wind Energy Association, 2005] and the need for short-term prediction [Pryor and Barthelmie, 2006]. At longer time scales (seasonal and beyond) it has relevance for planning and project economics. Given the high capital costs of most renewable energy systems relative to operation and maintenance and discounting of future revenues [Blanco, 2005], inter-annual variability can play a key role in dictating economic feasibility, hence “The importance
Contribution of variable renewable energy to increase energy security in Latin America

02 — Background

Climate change may also alter not only the wind resource, but also the environmental context, operation and maintenance and/or design of wind developments. A major issue in design of wind turbines and wind farms is to characterize wind turbine loads which affect the performance and lifetime of the turbines [Hau, 2006]. Loads relating to external conditions can be divided into extreme loads which arise mainly from extreme (i.e., inherently rare) events with return periods of 5–50 years and fatigue loads [Dekker and Pierik, 1999] which are primarily determined by the mean wind speed and the standard deviation of wind speed fluctuations that are strongly related to site turbulence levels [Frandsen et al., 2007]. Because of the complexity of interactions between wind turbines and turbine components with external conditions, structural dynamic models are used to assess loads based on a number of frequently updated design load cases [Hau, 2006].

We are not aware of any study that has sought to quantify possible changes in the parameters used in the design load cases for wind turbine design due to climate evaluation. However, changes in extreme loads which frequently arise from high-wind speeds [Moriaty, 2008] well may evolve as a result of changing storm intensity and tracking. Wind turbines are designed for different conditions [IEC, 2005] based on hub-height values of the mean annual wind speed, the reference (extreme) wind speed (highest mean 10-min-average wind speed value to be expected in a 30-year period) and the characteristic turbulence intensity to be expected at 19m/s [Hau, 2006]. Average turbulence levels are most strongly related to site characteristics such as roughness of the land surface (in the near surface wind flow) and surface wind roughness. The near surface wind flow may become more turbulent when the vegetation is removed or when the terrain is changed significantly. This has the potential to change the wind environment all over the Caribbean region [Conteras-Lisperguer and Cuba, 2008].

Overall, when considering the potential impact of climate change on wind energy potential, investing in wind energy systems presents significant challenges to local government and industry. The analysis did not consider the process of change projection modeling and economic assessment studies be performed in order to understand the extent to which climate change may affect a wind energy project and also determine what the long term financial viability may be [Conteras-Lisperguer and Cuba, 2008]. To the best of the author’s knowledge, no quantitative study of the possible impacts of climate change in the Caribbean was found in the scientific literature.

In relation to Brazil, more studies were found. LUCE-NA et al. (2015) used the ‘delta method’ to assess climate change impacts on wind generation potential in Brazil. The results of this study show that the wind potential will probably not suffer any negative impacts. On the contrary, for scenarios A1B and B1 results showed an increase in Brazil’s wind potential as time goes by. The Brazilian Northeast, as well as the coast of the North and Northeast ear regions are areas that have shown to be particularly well-suited to wind power exploitation. However, (A1B and B1) were dynamically downscaled in regional climate projections for Brazil by an expert team on Brazil climate change projection modeling and economic assessment studies be performed in order to understand the extent to which climate change may affect a wind energy project and also determine what the long term financial viability may be [Conteras-Lisperguer and Cuba, 2008].

The 8A storyline and scenario family describes a very heterogeneous world. The underlying theme is self-reliance and preservation of local identities. Ferryt patterns across regions converge very slowly, which results in continuously increasing global temperature increase. This is particularly true for areas with less available water like the desert and semiarid regions [INPE, 2007]. Such alterations could also influence wind potential in climate change scenarios.

Goubanova et al. (2016) used a statistical downscaling method to assess the regional impact of climate change on the sea-surface wind over the Peru–Chile upwelling region as simulated by the global coupled general circulation model IPSL-CM4. Taking advantage of the high-resolution QuikSCAT wind product and of the NCEP reanalysis, a statistical model based on multiple linear regressions is built for the daily mean meridional and zonal wind at 10 m for the period 2000–2008. The large-scale wind components and sea level pressure are used as regional climate predictors. The skill of the downscaling method is assessed by comparing with the surface wind derived from the ERS satellite measurements. In the work, wind data is extracted from the International Comprehensive Ocean-Atmosphere Data - ICOADS and through cross-validation. It is then applied to the outputs of the IPSL-CM4 model over stabilized periods of the pre-industrial, IPCC CO2 doubling (2 x CO2) and quadrupling (4 x CO2) climate scenarios relative to the pre-industrial simulations. The results indicate that surface air–shore winds off central Chile (off central Peru) experience a significant intensification (weakening) during Austral winter (summer) in warmer climates. This is associated with a general decrease in intra-annual variability.

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potential were based on wind’s average annual speed in km/h, compared for the time intervals considered by PERCIS.

LUCENA et al. (2010) indicate that the wind average speeds would increase considerably in coastal regions in general and particularly on the country’s North and Northeast regions. This study points to a greater frequency of wind at speeds over 8.5 m/s at the coast, which raises the possibility of including different turbine designs that may generate more power at higher speeds in future analyses. Results based on climate projections show that wind power generation could increase threefold in Brazil in scenario B2 and fourfold in scenario A2, when compared with the 2010 reference situation. However, these results are not definitive due to climate projection uncertainties and assumptions made in the study. In sum, this study indicates that wind power generation in Brazil will not be hindered by climate change.

Lucena, Szlko, and Schueffer (2009) provided a theoretical analysis of issues relevant to climate change impacts on wind power generation, such as the downscaling in speed distribution frequency, transposition of wind speed measuring height and possible alterations in wind occurrence. In addition, Prior and Barthelmie (2010) conducted a review of studies focused on climate change impacts (Global Climate Change) in wind power generation. They analyzed the mechanisms through which climate change may influence wind resources and its operational conditions, as well as the tools that have been employed to quantify these effects and uncertainties related to them.

In Pereira et al. (2013), climate change impacts on wind power are assessed by simulating future scenarios on the Brazil’s gross potential, taking into account climate scenarios of the IPCC SRES A1B emissions. The analysis was done for Brazil’s South and Northeast regions. Ground stations’ data trends were studied like wind frequency based on the global circulation model HadCM3. The ETA model was used to downscale a 40 km by 40 km resolution and 38 vertical layers. The ETA model was updated every 6 hours with the boundary conditions of the HadCM3 outputs.

This study, Pereira et al. (2013), employed observational data time series between 1961 – 2007 from selected national weather stations to seek for trends in wind speed. However, the search did not produce conclusive results. On the other hand, the ETA model predictions – HadCM3 for A1B scenario indicates an average growth trend from 15 to 30 per cent for onshore wind power density for most of Brazil’s Northeast region. Indeed, some regions showed an over 150 per cent increase, particularly the Northeast. In addition, with the exception of the country’s North and Northeast regions, the study pointed to a fall in future offshore wind power density, particularly off the coast of the state of Bahia.

Nevertheless, the same study pointed to a small increase in wind power density in Brazil’s South region, when compared with results for the Northeast. This means an average increase of 10 per cent, reaching over 20 per cent in some areas. The central region of the Rio Grande do Sul state, which extends to the south of Uruguay, showed a small decreasing trend in wind power. This region also showed the highest seasonal variability, with a global minimum in the austral summer (December-February) and an increase in the rest of the year, in relation to the baseline period. Therefore, according to PEREIRA et al. (2013), it is possible to expect that the impact of global climate change on wind power in Brazil’s Northeast and South may be favorable to existing and future projects in both regions. Table 4 summaries the studies cited above.

### 2.3.2. Impacts of Global Climate Change on Solar Resource

Massive solar power plants are likely to make a significant contribution to electricity generation in a possible low-carbon future. The calculation of electricity generation potential by PV technology is a basic step in analyzing scenarios for future energy supply. However, this future will also experience significant climate change caused by past and ongoing emissions of greenhouse gases and aerosols (Crook et al., 2011). Therefore, it is important not only to quantify the present solar resource but also to anticipate how the solar resource will change along with any climate change in the future (Burnett et al., 2014). This information will assist site choice, critical long-term energy output and financial calculations for future solar power plants (Crook et al., 2011). The implications of possible changes in usable wind and solar potential must be well understood for future planning purposes (Hegel et al., 2007).

It is ironic that much of the motivation to use renewable sources of energy generation comes from the desire to mitigate climate change, and climate change directly affects renewable energy resources (Burnett et al., 2014). Climate change can affect solar energy resources by changing atmospheric water vapor content, cloudiness and cloud characteristics, which affects atmospheric transmissivity (Cutforth et al., 2007). Cloudiness is strongly influenced by local temperature gradients as well as large-scale climate oscillations. Land surface changes can also affect local cloudiness and could be amplified in urban areas (Dennem et al., 2007), but making connections between climate change and changes in solar irradiation is a complicated matter (Hegel et al., 2007). In the case of solar energy, cloud cover is the most important property of the climate to consider. The increase in atmospheric particles (aerosols) can, in turn, increase cloud cover by providing greater numbers of cloud condensation nuclei. Global solar irradiance levels depend on the cloud cover characteristics, and therefore will change due to climate change (Burnett et al., 2014).

These modifications can have effects on electricity generation from photovoltaic and concentrated solar power (CSP) arrays (Sachse et al., 2012). Changes in PV output and its fractional contributions from temperature and irradiation are all very location dependent. The ambient temperature affects the electrical efficiency of a solar photovoltaic cell. While climate data on cloudiness from climate models may be difficult to obtain, the relation between temperature and photovoltaic efficiency is well documented. For most PV cell materials, PV output has a near linear response to cell temperature with a negative gradient, and an approximately proportional response to total irradiance except under low levels (Crook et al., 2013). A 3% reduction in global solar radiation would reduce solar PV cell output by 6%, these projections significantly impact solar energy generation and cost-effectiveness (Contreras-Lisperguer et al., 2008).

The efficiency of concentrated solar power (CSP) can also be impacted by climate change, as it consists of a thermal machine and, as such, its efficiency is altered by ambient temperature variations. CSP output has an approximately linear response to ambient temperature with a positive gradient. Furthermore, CSP based on solar electric generation systems (SEGS) operate a Rankine cycle and, therefore, is exposed to the increased water use and lower efficiency (Sachse et al., 2012). Not only temperature variations, but also changes in direct irradiation affect CSP output, with an approximately proportional response to direct irradiance (Crook et al., 2011). CSP does not utilize diffuse irradiance whereas non-concentrating PV utilizes both direct and diffuse irradiance. Irradiance...
is largely a function of cloud cover and cloud properties. Climate change will impact regional patterns of temperature and irradiance, and therefore affect regional PV and CSP output [Crook et al., 2011].

Other climatic variables have a notable impact on PV output. The wind influences the output of PV because forced convection removes heat from the cell and therefore reduces the cell temperature, increasing its efficiency. Dust settling on PV panels and solar collectors is a significant problem in more arid regions, while rainfall cleans the panels by removing dust [Crook et al., 2011], so the change in these climatic variables would also modify PV output.

There has been some previous work all over the world trying to measure the effects of climate change on solar energy. Fant et al. [2016] showed a method that introduces uncertainty from emission scenarios, climate sensitivity, and regional climate outcomes. A statistical model was used to expand upon a hybrid approach to include solar parameter estimates, efficiently producing a portfolio of possible outcomes. They found a wide range to the distributional as well as regional results. These differences were a result of model-response disparity as well as the choice of emission scenarios. Nevertheless, the results of this study indicated that the long-term mean solar resource potential would most likely keep unchanged by 2050 [Fant et al., 2016].

The study conducted by Gunderson et al. [2014] evaluated the current and future solar energy potential through the use of grid-connected PV power plants near the Black Sea region. Incident solar radiation flux from re-analyses, spatial interpolation, and the application of the Delta change method were used to assess the current and future solar resource potential. They simulated data to determine potential change in climate and land-use according to two different development scenarios. The results of Gunderson et al. [2014] showed that the solar resource is sufficient for solar PV power installations in the Black Sea region. Incident solar radiation flux from re-analyses, spatial interpolation, and the application of the Delta change method were used to assess the current and future solar resource potential. They simulated data to determine potential change in climate and land-use according to two different development scenarios. The results of Gunderson et al. [2014] showed that the solar resource is sufficient for solar PV power installations in the Black Sea region and the results also suggested that the solar resource is not expected to vary greatly over the next century over the Black Sea region, some uncertainties remain. However, it is possible to conclude that land-use changes will have a significant impact on suitable sites for PV power generation [Gunderson et al., 2014].

According to Schaeffer et al. [2012], impacts on climatic variables may have different trends around the world and the same applies to solar energy resources, having positive impacts in terms of increase in solar radiation in some situations (e.g., a decrease trend in incoming solar radiation in Canada [Cutforth et al., 2007]).

In Burnett et al. [2014], they characterized the UK solar resource for both the present and future climates providing a detailed assessment. The present solar irradiation level was assessed through the conversion of 30 years of observed historical monthly average sunshine duration data. After combining this with the UKCP09 probabilistic climate change projections, they examined the effect of climate change to give estimates of the future UK solar resource. They found that climate change would increase the average resource in the south of the UK, while marginally decreasing it in the Northwest. The overall effect was a mean increase of the UK solar resource; however, it would have greater seasonal variability and discrepancies between geographical regions [Burnett et al., 2014].

Crook et al. [2011] calculated how climate change was likely to alter the output of photovoltaic and concentrated solar power plants over the next 80 years, taking a global perspective. Established computer models indicated that changes in solar power plant output would show considerable regional differences. For example, PV generation was likely to increase significantly in Europe and China, but decrease in many parts of the world such as western America and the Middle East. This is caused by either a change in temperature or insolation, with considerable regional differences. CSP output is likely to increase by more than 10% in Europe, increase by several percent in China and a few percent in Algeria and Australia, and decrease by a few percent in western USA and Saudi Arabia. This demonstrates that CSP is usually more sensitive to climate change than PV, although there are strong regional differences [Crook et al., 2011]. Figure 2 to Figure 4 present a series of maps showing the absolute change in temperature and insolation (total and direct), all over a 10-year mean centered on 2080. The data presented is from the HadGEM1 model.

It is important to note that there is a lack of data regarding impacts of climate change on solar resources in Latin America and the Caribbean. The use of solar energy in the Caribbean is widely known and disseminated, but only on a local scale or for domestic uses [Contreras-Lisperguer et al., 2008]. As the quantity of solar plants in Caribbean and South America is still incipient, the interest in this kind of study is still growing for the region.

In many studies about climate change impacts the authors mention the uncertainties related to these works (Gunderson et al., 2014, Crook et al., 2011, Fant et al., 2016). Some of them assert that these uncertainties are due to the use of GCMs [Fant et al., 2016] and some authors suggest, for future studies, developing a similar
Contribution of variable renewable energy to increase energy security in Latin America

Due to growing concern about climate change, fossil energy sources are increasingly being encouraged to be traded for clean energy, including hydroelectricity. However, changes in climatology, by reason of climate change, are often not considered in alternative energy projects. Variation in both rainfall and temperature can affect energy production [Mukheibir, 2013].

Among the consequences of climate change, one can expect a drop in water quality in general, as well as risks to the quality of drinking water, despite conventional treatment, due to interconnected factors like: temperature increase; increase in sediments, nutrients and pollutants loads from strong rainfall; increase in pollutant concentration during droughts; and interruption of treatment facilities during floods [IPCC, 2014]. According to the IPCC, there is strong evidence that climate change will reduce surface and underground hydro resources in most dry subtropical areas, during the 21st century. This problem can cause competition for water between the economic sectors, like agriculture and industry.

Flow variation in rivers and levels of lakes caused by global climate change can impact the generation of electricity athwart hydraulic power [Chiew, 2016]. It also depends on alterations in volume, intensity and rainfall time, that is occasioned by evapotranspiration, which is function of temperature, insolation, wind speed and atmospheric humidity. The answer to changes in climate variation is different among the distinct river basins, depending on their hydrological and physical characteristics, as also of the amount of water stored on the surface and underground [Kundzewicz et al., 2008]. Climate change will affect the function and operation of flood control, drainage and irrigation systems, and change water resource management. There is another preoccupation, because we cannot simply use past hydrological experience to predict future conditions [Lucena, 2010].

The concern with changes in weather conditions started in the 1960s. However, the first studies on the hydrological impacts of climate change began in 1980 [Nemec; Schaeck, 1982]. This is one of the areas that the international scientific literature has paid more attention to. The importance of the hydrological cycle came to light in the Generation Circulation Model (GCM) results. GCM is the baseline for most studies on climate change impacts on water resources, which relates chemical alterations in the atmosphere with great climate variation.

The limitations of models that study the impact of global climate change on hydrological systems are mainly the spatial scale, but also the representation of extreme weather events on larger scales, vegetable cover and absence of mention of extreme events such as droughts and floods [Lucena, 2010]. Another problem is the small number of studies with analysis of climate change impacts on underground water, including the uncertainty in the relationship between surface and underground rivers [Alley, 2001; Kundzewicz, 2007]. There are few papers on the theme of climate change on water resources that focus on Latin America. When they approach this region, most of these cases are reported from Brazil.

In Salatti et al. [2010], the HadRM3P model calculated the Brazilian water balance between 2011 and 2100 for scenarios A2 and B2, compared with the period 1961-1990, designated as the reference. The results are really worrisome, with a dramatically drop in flows by 2100 in the East Atlantic and Eastern Northeast basins, coming close to zero.

The same model was integrated by Marengo et al. [2010] to obtain the climatology model for the present time (1961-1990) and then, to future projections (2071-2100) for scenarios A2 and B2. This study concludes that the Amazon and the Northeast are the most vulnerable areas in Brazil. Average warming may reach 5 °C in 2100 in scenario A2 and 1 °C in B2, although gradual temperature increase in the Amazon could reach 7-8 °C or 4-6 °C in 2100, respectively. For the whole country, the tendency is an increase in temperature and extreme heat, as well as a reduction in the frequency of frost, due to a rise in the minimum temperature, particularly in the south, south-east and mid-west states. However, in all of the scientific literature on climate change impacts on water resources...
es, there is a trend in the Brazil regions: an increasing frequency and intensity of extreme events, higher water stress in the Northeast, large falls in rainfall in the Amazon region and small flow increases in the south's basins. According to Soito and Freitas (2011), vulnerability and adaptation of water resources is related to average trends and also variability alterations in hydrological systems or extreme events, when global climate change is present. The study points out that in the projections made so far, results for South America have not agreed with respect to flow predictions. First of all, because of rainfall prediction differences and, secondly, as a consequence of differing evaporation values. In the same way, in countries exposed to water stress, a negative effect on the flow of rivers, and the relling of underground water reservoirs and aquifers is expected from climate change.

The impacts of climate change on hydropower generation come from alterations in flow variation or in the seasonality regime. The vulnerability of a hydropower plant depends on the water storage capacity of reservoirs [Schaef er et al., 2012; Lucena et al., 2009]. It affects the impacts on electricity generation are not proportionate impacts on flow, because of the water storage capacity of reservoirs in Brazilian plants.

Central America is one of the most vulnerable regions to climate change. The region is strongly affected by extreme temperature and precipitation events due to its geographical location. This often leads to droughts and floods, which tend to increase further in the coming years, according to models that study climate change. Due to the high dependence of hydropower dams for electricity generation in the region, more than 50% in 2015, it is very important to identify the possible impacts of climate change on the flow of rivers that allow the production of energy in these hydropower plants [IDB, 2016].

In the IDB study (2016), seven Central American countries were studied: Belize, Costa Rica, El Salvador, Guatemala, Honduras, Nicaragua and Panama. In future projections in this region, electricity production will fall 19.6% in 2020 and 26% in 2050 with an increase of 3.2 °C in the average temperature, between 2060 and 2090. In this scenario the droughts will be more frequent and the maximum flows will fall during the XXI century.

A key region in Central America that is vulnerable to impacts of climate change is the Rio Lempa basin, the largest river system in Central America, which includes El Salvador, Honduras and Guatemala. Maurer et al. [2009] analyzed hydrologic impacts of projected climate changes on Rio Lempa Basin and the inflow variation of two major hydropower reservoirs, due to changes in temperature and precipitation from 16 climate models using two emissions IPCC scenarios (B1 and A2) during 2040-2069 and 2070-2099. The results indicated a decrease in hydropower generation from two hydropower projects: Cerrón Grande in Rio Lempa basin (El Salvador) and Chixoy in Chinoy basin (Guatemala). They used the following GCMs: HADCM3, GFDL, Ryo and ECHAM4 for scenario B2 and HADGEM2, GFDL CM2.0 y ECHAM4 for scenario A2. The variation of temperature and precipitation was projected for the years 2020, 2050, 2070 and 2100, and changes in streamflow was simulated in software Water and Power Potential (WAPPO).

The projected results for A2 scenario found a reduction in the Chiyoy’s power generation of approximately 25% in 2020, 57% in 2050, 47% in 2070 and 6% in 2070 and 8% in 2010 in comparison of average power generation from 1979 to 2008. Regarding the Cerrón Grande hydropower plant the projected decrease in electricity generation is 22% in 2020, 34% in 2050, 41% in 2050, 57% in 2070 and 71% in 2010, compared to average generation between 1984 to 2009. In B2 scenario an increase of 4% and 6% in electricity generation was expected for 2020 in Chixoy and Cerrón Grande, respectively. However, in the following years the results again indicate a decrease in energy production that will reach 26% in Chixoy and 17% in Cerrón Grande in 2010.

Despite the negative impacts mentioned above, the study carried out by Popescu et al. [2014] has resulted in an increase in potential hydropower as a result of climate change in La Plata Basin. Located in five countries: Argentina, Brazil, Bolivia, Paraguay, Uruguay. Popescu et al. [2014] studied the impact of hydrological changes on hydropower production in La Plata Basin based on PROMES-UCLM and RCA-SMH climate change scenarios. The study used projected climate parameters from two regional climate models as an input of a hydrological rainfall – runoff model for the time slots of 2011-2050 and 2079-2089. Results showed an increase of the hydropower energy potential for both periods.

Hydropower generation in Amazonia will be more vulnerable in the dry season, challenging future energy security across the region that has many hydropower projects without reservoirs like Belo Monte in Brazilian Amazonia [Lucena et al., 2011].

In Brazil, the main projected impact was a drop in the system’s reliability and extreme hydropower generation effects in the North and Northeast regions [Lucena et al., 2009]. In this study, the South and Southeast basins have a positive variation in firm energy. So, the aggregate average energy keeps regular. But in Paranáiba and East Atlantic basins, water surplus fall in 80 per cent in some points of the projections, with a dramatically drop in energy production.

According to IPCC [2014], in many regions, changes in rainfall or the melting of snow and ice are altering hydrological systems and affecting water resources in terms of quantity and quality. Glaciers are shrinking almost all over the world and permafrost is melting in high altitude and latitude regions due to climate change, affecting the flow of available water resources. In South America, hydropower is the main source of renewable energy and has an important role in the electric sector. Therefore, if climate change affects hydric plants, this will concern all of the electrical energy system [Zwan et al., 2016]. Table 6 summarizes the studies cited above.

### Table 6. Summary of studies assessing the impacts of climate change on hydropower resource

<table>
<thead>
<tr>
<th>Study</th>
<th>Region</th>
<th>Effects</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>CEPAL (2012)</td>
<td>Brazil</td>
<td>Decrease in energy production (more than 50% generated by hydroelectricity generation), between 2060 and 2099</td>
<td></td>
</tr>
<tr>
<td>Salati et al. (2010)</td>
<td>Brazil</td>
<td>Climate impacts on water balance at Brazil’s basins projected for the 21st century considering two IPCC scenarios (A2 and B2). The results indicate a drastic fall in flows by 2090 in the East Atlantic and Eastern Northeast basins</td>
<td></td>
</tr>
<tr>
<td>Marengo et al. (2010)</td>
<td>Brazil</td>
<td>Impacts on hydropower generation in Central America.</td>
<td></td>
</tr>
<tr>
<td>IDB (2016)</td>
<td>Brazil</td>
<td>Results indicate 39.5% of fall in electricity production (more than 50% generated by hydroelectricity generation), between 2060 and 2099</td>
<td></td>
</tr>
<tr>
<td>Lucena et al. (2009)</td>
<td>Brazil</td>
<td>Impact of climate change in the Brazilian region.</td>
<td></td>
</tr>
</tbody>
</table>

The main impact is a drop in the reliability and extreme hydropower generation effects in the North and Northeast regions. In Paranáiba and East Atlantic basins, water surplus fall in 80 per cent in some points of the projections, with a dramatically drop in energy productions. |
This study aims to determine the possible impacts on the future long-term wind and solar energy resource complementarity caused by climate change in selected regions of the LAC. This study focuses on the annual seasonality of the wind and solar energy resources. Based on the climate projections for the IDB database, the energy complementarity was re-evaluated between the areas that showed complementarity in the first report of this study.

The flowchart below shows the steps taken to achieve the goal of the study. The assumptions and procedures of each step are described hereafter.
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**SECTION II**

**Methodology**

### a) GCM/RCP Data

To develop the climate projections, MIROC-ESM-CHEM and HadGEM2-ES General Circulation Models (GCMs) were considered. The choice of the GCMs was based on studies performed in Brazil by CHOU et al. [2014a, 2014b], who used these models to research downscaling of the results obtained from the GCMs for South America.

The GCM results were obtained from the Inter-Sectoral Impact Model Integration and Intercomparison Project (IS-Impact v2 phase 2) database version 20160708, which were processed by HEMPLE et al. [2013]. The variables used are the short wave downwelling radiation – rds (Wm\(^{-2}\)) and the near-surface wind magnitude – wind speed (ms\(^{-1}\)).

For each GCM, two Representative Concentration Pathways were chosen: i) the RCP 4.5 scenario, that represent a stabilization scenario in which total radiative forcing is stabilized before 2100 and ii) the RCP 8.5 scenario that represents increasing greenhouse gas emissions over time, this scenario can be the most pessimistic scenario for wind and solar resources [RIAI et al., 2011].

The RCP4.5 is an intermediate emission/radiative forcing, which integrates lower energy intensity, strong reforestation programs, dietary changes and stringent climate policies. The RCP8.5 is a high emissions/radiative forcing scenario, which combines assumptions about high population and relatively slow income growth with modest rates of technological change and energy intensity improvements, leading in the long term to high energy demand and GHG emissions in the absence of climate change policies [RIAI et al., 2011].

### b) Database Treatment

The IDB database comprises 36 areas with high potential solar PV resources and 50 high potential wind energy resources (hotspots). The results of the Report I Part I indicate the areas that presented a seasonal complementarity. Thus, these pairs of hotspots are the focus of this second report and of Part II and are shown in Table 7.

The GCMs results for the wind speed (near-surface wind magnitude – wind (m.s\(^{-1}\))) were extrapolated to estimate the wind speed at a standard wind turbine height (100m) using the Power Law [KUBLIK et al., 2011] which is an empirical equation expressed in (Eq. 2).

\[ u_z = \alpha u_1 \left( \frac{z}{z_1} \right)^{1/7} \]  

(Eq. 2)

Where \( \alpha \) is the wind shear coefficient, for neutral stability conditions this coefficient is approximately 1/7, \( u_z \) is the wind speed at the reference height \( z \), and \( u_1 \) is the extrapolated speed at the height \( z_1 \).

Once the wind speed data is extrapolated, the monthly value (median) for each resource (wind speed and solar irradiation) is calculated, both for IDB database and for GCM simulations. The GCM simulation results are composed by the historical simulated data (model runs for the 1961-2004 period) and the future climate projections (2005-2099). The climate projections were clustered in 3 groups: i) 2010-2040, ii) 2041-2070, iii) 2071-2100.

### c) IDB Database versus GCM Historical Data

As mentioned, two GCMs were considered, the HAD-GEM2-ES and MIROC-ESM-CHEM. With the aim of selecting the GCM that best represent the IDB database, a comparison between the two GCM historical data (1961-2004) and the IDB data was made. This comparison was made between "equivalent" years.

An "equivalent" year was created for the IDB data as well as for each of the GCMs historical data. It was obtained through (Eq. 3).

\[ EY_{i} = \frac{\text{median} \ ( \text{Data}_i )}{\text{month} \ i < T} \]  

(Eq. 3)

Where \( EY \) is the equivalent year, \( i \) is the month, \( Data \) is the resource value, \( i \) is the year and \( T \) is the period of analysis.

This study defined two decision criteria to determine which GCM simulation historical data best represent the historical IDB database: i) the determination coefficient

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**Table 7. Seasonal complementarities obtained in Report I.**

<table>
<thead>
<tr>
<th>Wind Pot. IDB</th>
<th>Solar PV IDB</th>
</tr>
</thead>
<tbody>
<tr>
<td>WIND_VE_A01</td>
<td>SOLAR_VE_A01</td>
</tr>
<tr>
<td>WIND_VE_A02</td>
<td>SOLAR_VE_A02</td>
</tr>
<tr>
<td>WIND_VE_A03</td>
<td>SOLAR_VE_A03</td>
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<tr>
<td>WIND_VE_A04</td>
<td>SOLAR_VE_A04</td>
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<tr>
<td>WIND_VE_A05</td>
<td>SOLAR_VE_A05</td>
</tr>
<tr>
<td>WIND_AR_A01</td>
<td>SOLAR_AR_A01</td>
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<tr>
<td>WIND_AR_A02</td>
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<td>WIND_AR_A03</td>
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<td>WIND_AR_A04</td>
<td>SOLAR_AR_A04</td>
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<tr>
<td>WIND_AR_A05</td>
<td>SOLAR_AR_A05</td>
</tr>
<tr>
<td>WIND_BR_A01</td>
<td>SOLAR_BR_A01</td>
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<tr>
<td>WIND_BR_A02</td>
<td>SOLAR_BR_A02</td>
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<td>WIND_BR_A03</td>
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<tr>
<td>WIND_BR_A04</td>
<td>SOLAR_BR_A04</td>
</tr>
<tr>
<td>WIND_BR_A05</td>
<td>SOLAR_BR_A05</td>
</tr>
</tbody>
</table>
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Nagelkerke, 1991] that provides a measure of how well a model replicates the “observed” data and ii) the correlation coefficient [Kougias et al., 2016] that, in this case, measures the strength and direction of the linear relationship between the IDB database and the GCM historical data.

d) Delta Factor Definition

As mentioned, the climate projections were clustered in 3 groups: i) 2010-2040, ii) 2041-2070, iii) 2071-2100. An “equivalent” year for each one of these groups was created using (Eq. 3). The delta factors were defined for each GCM climate projections (RCP 4.5 and RCP 8.5).

A monthly delta factor will be applied to these “equivalent” years. The delta factor to be applied is defined by (Eq. 4).

\[ \delta_{m,p} = \frac{EY_{m,p} - EY_{m}}{EY_{m}} \]

such that \( p = \{p_1, p_2, p_3\}, m = \{1, 2, ..., 12\} \) (Eq. 4)

Where \( p_1 \) represents the 2010-2040 cluster, \( p_2 \) represents the 2041-2070 cluster, \( p_3 \) represents the 2071-2100 cluster, \( m \) is the month analyzed, \( EY_{m,p} \) is the equivalent year of the GCM climate projections and \( EY_{m} \) is the equivalent year of the GCM historical data.

e) Future Climate Projections (2010-2100) for Latin America

As it was pointed in section 2.2, climate scenarios make implicit or explicit assumptions about the extrapolation of climate model biases from current to future time periods. Such assumptions are inevitable because of the lack of future observations and, being subjected to different sources of uncertainty [Kerkhoff et al, 2014]. Therefore, a sensitivity analysis was made between each monthly value of the cluster projection period with the monthly historical value for the chosen GCM. The result of this variation is called, in this study, the “delta factor”.

The monthly delta factor is applied to the equivalent year obtained from the IDB database, (Eq. 3). In this way, the variability in the gridded observations is preserved and the comparison between future scenarios and historical modeled is straightforward and easily interpreted.

\[ NP_{p} = \delta_{m,p} \times EY_{m} \] (Eq. 5)

It is important to highlight that for a coherent use of the delta factor, it is necessary that the historical database simulations are aligned with the seasonal pattern of the resource i.e. the resource data of historical GCM and IDB must have good seasonal consistency.

f) Future Energy Complementary in LAC

The renewable energy resources complementarity in LAC, obtained in the report I, is reviewed in order to identify possible impacts as a consequence of climate change. The potential complementarity between resources is evaluated by the linear correlation method, Pearson method.
Results

The historical simulation data of HadGEM2-ES and MIROC-ESM-CHEM with scenarios of RCP 4.5 and RCP 8.5 were considered for this Report. A statistical analysis was made to check the seasonal consistency between the simulated historical GCM versus the IDB database. The seasonal patterns were built using the monthly medians of each database available.
The comparison between IDB database and the GCMs data was based on the correlation factor, to determine the strength and direction of the linear relationship between the IDB database and the GCM historical data, and the ordinary least square (OLS) method in order to assess the goodness of fit measured by the coefficient of determination R². The analysis using the correlation factor was inconclusive since for each area that was considered, the correlation factor presented a similar value for both GCM models. The results using OLS were more enlightening.

Appendix 7.1 shows the equivalent year monthly pattern of the historical databases and their R² coefficient and correlation values, for the areas that presented energy complementary in the first report of this study. This process indicated that most of the area analyzed had a good seasonal consistency, except for two areas: (i) SOLAR_ES_A01 had different seasonality between the months of fall and spring; (ii) WIND_CL_A01 did not show the same seasonality for the whole period analyzed. It is not possible to assess future impacts on the complementarity when the historical GCM simulation is not adjusted to the original data resource. Therefore, the correlation of WIND_CL_A01 & SOLAR_MX_A01 was not considered for the analysis.

Additionally, the OLS analysis was done over the whole set of data, the statistical parameters are exposed in Table 8. This study chooses to work with the HadGEM2-ES as it presented a better fit for the IDB database.

4.1 Trend Analysis in the Solar Radiation and Wind Speed Resources for the selected cases of Latin America

The use of the delta factor helps to analyze possible future projection of the renewable energy resources i.e. solar radiation and wind speed resources. In this section the delta factor impact of the two scenarios (RCP4.5 and RCP8.5) in the renewable energy resource will be analyzed. In other words, the main findings of the possible trend of the resources are described. The analysis was based on HadGEM2-ES model. The delta factor for each hotspot is presented in the appendix 7.1 and the trend of the resources of the selected areas is shown in appendix 7.5.

For both scenarios, RCP 4.5 and RCP 8.5, the solar resource of the hotspots did not show a significant variation in the average irradiation during the period of analysis on a yearly basis. These results are coherent with the discussion made in the section 2.4.2. The exceptions were for Solar_EC_A01, that from the year 2040 and for both scenarios, the radiation in that area show increasing trend. The SOLAR_PA_A01 area presented a small decrease in the solar radiation for the whole period of analysis, especially in the RCP 8.5 scenario.

Additionally, in a seasonal analysis, for the RCP 4.5 scenario, the solar radiation shows an increase during the winter (Jun-Aug) in the following areas: SOLAR_EC_A01 (2010-2020) and SOLAR_VE_A01 (2020-2050). The SOLAR_BR_A03 area presents a decrease for the summer (Dec-Feb) for the period of 2010-2010. In the case of RCP8.5 the results for SOLAR_BR_A03 show a decrease, when compared to historical data, during the summer and an increase during the winter, it occurs for the whole analyzed period. For SOLAR_MX_A01, the solar irradiation presents a decrease for the winter and an increase during the summer for the period of 2040-2100.

On the other hand, in the RCP 4.5 scenario the wind speed resource shows a variation in the annual seasonality. For instance, the seasonal analysis using the delta factors shows a decrease in the monthly average wind speed of WIND_BR_A04 and WIND_BR_A05, especially in the period of 2010-2070. On the other hand, the wind hotspots in Ecuador and Venezuela show a trend of increasing wind speed during the whole period of analysis.

In the case of scenario RCP8.5, during the period 2010-2040, the average wind speed of the areas WIND_CO_A01, WIND_BR_A01, WIND_EC_A01, WIND_PE_A01 and WIND_BR_A05 shows a decrease when compared to the historical model on a yearly basis. However, 66% of the wind hotspot showed a strong tendency to have higher wind speeds after 2040. In all of the cases the increase in wind speed is stronger during the RCP 8.5 scenario. WIND_BR_A01 and WIND_BR_03 are the areas that present the most intensive delta.

4.2 Climate Change Impact on Energy Complementarities – Analysis based on a Seasonal Approach

To assess the impact of global climate change on wind and solar complementarity, it was necessary, based on the climate projection of the HadGEM2-ES (RCP4.5 and RCP8.5), to create scenarios that would show the future behavior of the wind and solar resources. In Latin America; these scenarios were built using the delta factors defined by (Eq 4) and presented in Appendix 7.2.

Based on the climate projections for the IDB database, the energy complementarity was re-evaluated between the areas that showed a complementarity in the first report of this study.

As the Table 10 and Table 11 will show, the behavior of the climate change projection complementarities for the period of 2010-2040 based on the RCP4.5 are similar to the ones based on the RCP 8.5. The exception were WIND_PE_A01 & WIND_CO_A02, whose complementarity remained unchanged during the RCP 4.5 scenario but decreased for the RCP 8.5 scenario and WIND_PE_A01 & WIND_BR_A01 whose complementarity increased in the RCP 8.5 but decreased in the RCP 4.5. For the periods of 2041-2070 and 2071-2100 the complementarities between scenarios differ greatly.

Appendix 7.2 presents the behavior of each one of the areas that presented complementarity for each period of time (2010-2040, 2041-2070, 2071-2100) for the scenarios RCP 4.5 and 8.5. The main findings are presented in the next two sections.

4.2.1 Climate Change Impact on Energy Complementarities – RCP 4.5

In this section the main findings for the energy complementarities based on HadGEM2-ES model and RCP4.5 are presented.

- In this scenario, for the period of 2010-2040, 47.5% of the selected cases had no significant variations regarding the historical complementarity and 36.8% improved. For the period of 2041-2070 the numbers were 47.5% and 31.5% respectively and for the period of 2071-2100 the numbers were 47.5% and 26.3%.
- Even though during the whole period of analysis (2010-2040), the area proportion of the energy complementarities remained unchanged or even increased, the number of areas that show a reduction in their correlation factor, as the years get closer to 2100, increased. For the period of 2010-2040, 16% of the selected cases show a decrease in their complementarity, 21% for 2041-2071 and 16% for 2071-2100. This means that the complementarity of fourteen pairs of hotspots remained around or higher than the historical value for the whole period analyzed (projection for 2010 until 2100).
- Five pairs of hotspots the complementarities were lower than the historical value in the last period of the analysis: WIND_VE_A01 & WIND_BR_A05, SOLAR_BR_A03 & WIND_BR_A01, SOLAR_VE_A01 & WIND_AR_A01, SOLAR_VE_A03 & WIND_EC_A01, WIND_SU_A01 & WIND_BR_A04.
- There were no cases in which the polarity of the correlation factor changed to a positive correlation.

Table 11 summarizes the impact of climate change, based on HadGEM2-ES model and RCP4.5 scenario, in the renewable energy complementarity between the hotspot areas, categorizing the increments with no significant variations and decrements.

Table 9. Climate Change Impact on Energy Complementarities based on HadGEM2-ES model and RCP4.5 scenario

In this section the main findings for the energy complementarities based on HadGEM2-ES model and RCP8.5 are presented.

- In 84% of the selected cases, the complementarity, for the time period of 2010-2040, improved or had no significant variations regarding the historical complementarity; the figure was 61% for the period of 2041-2070. Moreover, for three pairs of hotspots (WIND_VE_A03 & WIND_BR_A04, WIND_SU_A01 & WIND_BR_A03 and SOLAR_PA_A01 & WIND_AR_A01) the complementarity remained around or higher than the historical value for the whole period analyzed (projection for 2010 until 2100). For the long term planning this result could encourage the expansion of solar and wind projects since no strong variation in the generation profile is expected.
- SOLAR_BR_A03 & WIND_BR_A01 and WIND_PE_A01 & WIND_CO_A02 are special cases in which the polarity of the correlation factor changed to a positive correlation, the first one in the period of 2071-2100 and the second one in the period of 2010-2040.
- The 2071-2100 period stands out by the strong decrease tendency (68% of the cases) in the energy complementarities.
Table 9. Climate Change Impact on Energy Complementarities based on HadGEM2-ES model and RCP4.5

<table>
<thead>
<tr>
<th>Year Period</th>
<th>Increment (the correlation factor became more negative by 5%)</th>
<th>No significant variation (less than 5%)</th>
<th>Decrement (the correlation factor became more positive by 5%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2010-2040</td>
<td>WIND_VE_A04 &amp; WIND_BR_A04</td>
<td>WIND_VE_A04 &amp; WIND_BR_A04</td>
<td>SOLAR_BR_A03 &amp; WIND_BR_A01</td>
</tr>
<tr>
<td></td>
<td>WIND_BR_A05 &amp; WIND_BR_A01</td>
<td>WIND_VE_A05 &amp; WIND_BR_A05</td>
<td>SOLAR_BR_A03 &amp; WIND_BR_A05</td>
</tr>
<tr>
<td></td>
<td>WIND_BR_A01</td>
<td>WIND_VE_A01 &amp; WIND_BR_A01</td>
<td>WIND_VE_A01 &amp; WIND_BR_A01</td>
</tr>
<tr>
<td>2041-2070</td>
<td>WIND_VE_A04 &amp; WIND_BR_A04</td>
<td>WIND_VE_A05 &amp; WIND_BR_A05</td>
<td>WIND_VE_A05 &amp; WIND_BR_A05</td>
</tr>
<tr>
<td></td>
<td>WIND_BR_A05 &amp; WIND_BR_A01</td>
<td>WIND_VE_A01 &amp; WIND_BR_A01</td>
<td>WIND_VE_A01 &amp; WIND_BR_A01</td>
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<td>WIND_VE_A01 &amp; WIND_BR_A01</td>
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</tr>
<tr>
<td>2071-2100</td>
<td>WIND_VE_A04 &amp; WIND_BR_A04</td>
<td>WIND_VE_A05 &amp; WIND_BR_A05</td>
<td>WIND_VE_A05 &amp; WIND_BR_A05</td>
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<td>WIND_VE_A01 &amp; WIND_BR_A01</td>
<td>WIND_VE_A01 &amp; WIND_BR_A01</td>
</tr>
</tbody>
</table>

Table 10 summaries the impact of climate change, based on HadGEM2-ES model and RCP8.5 scenario, in the renewable energy complementarity between the hotspot analyzed, categorizing the increments, no significant variations and decrements.

Table 10. Impacto del cambio climático en las complementariedades energéticas en base al modelo HadGEM2-ES y el escenario RCP8.5

<table>
<thead>
<tr>
<th>Year Period</th>
<th>Increment (the correlation factor became more negative by 5%)</th>
<th>No significant variation (less than 5%)</th>
<th>Decrement (the correlation factor became more positive by 5%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2010-2040</td>
<td>WIND_VE_A04 &amp; WIND_BR_A04</td>
<td>WIND_VE_A05 &amp; WIND_BR_A05</td>
<td>SOLAR_BR_A03 &amp; WIND_BR_A01</td>
</tr>
<tr>
<td></td>
<td>WIND_BR_A05 &amp; WIND_BR_A01</td>
<td>WIND_VE_A01 &amp; WIND_BR_A01</td>
<td>WIND_VE_A01 &amp; WIND_BR_A01</td>
</tr>
<tr>
<td></td>
<td>WIND_BR_A01</td>
<td>WIND_VE_A01 &amp; WIND_BR_A01</td>
<td>WIND_VE_A01 &amp; WIND_BR_A01</td>
</tr>
<tr>
<td>2041-2070</td>
<td>WIND_VE_A04 &amp; WIND_BR_A04</td>
<td>WIND_VE_A05 &amp; WIND_BR_A05</td>
<td>WIND_VE_A05 &amp; WIND_BR_A05</td>
</tr>
<tr>
<td></td>
<td>WIND_BR_A05 &amp; WIND_BR_A01</td>
<td>WIND_VE_A01 &amp; WIND_BR_A01</td>
<td>WIND_VE_A01 &amp; WIND_BR_A01</td>
</tr>
<tr>
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<td>WIND_VE_A01 &amp; WIND_BR_A01</td>
<td>WIND_VE_A01 &amp; WIND_BR_A01</td>
</tr>
<tr>
<td>2071-2100</td>
<td>WIND_VE_A04 &amp; WIND_BR_A04</td>
<td>WIND_VE_A05 &amp; WIND_BR_A05</td>
<td>WIND_VE_A05 &amp; WIND_BR_A05</td>
</tr>
<tr>
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<td>WIND_BR_A05 &amp; WIND_BR_A01</td>
<td>WIND_VE_A01 &amp; WIND_BR_A01</td>
<td>WIND_VE_A01 &amp; WIND_BR_A01</td>
</tr>
<tr>
<td></td>
<td>WIND_BR_A01</td>
<td>WIND_VE_A01 &amp; WIND_BR_A01</td>
<td>WIND_VE_A01 &amp; WIND_BR_A01</td>
</tr>
</tbody>
</table>
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<table>
<thead>
<tr>
<th>2010-2040</th>
<th>[2041-2070]</th>
<th>[2071-2100]</th>
</tr>
</thead>
<tbody>
<tr>
<td>SOLAR_BR_A03 &amp; WIND_VE_A03 &amp; WIND_VE_A04 &amp; WIND_VE_A02 &amp; WIND_BR_A03</td>
<td>SOLAR_BR_A01 &amp; WIND_VE_A03 &amp; WIND_VE_A04 &amp; WIND_VE_A02 &amp; WIND_BR_A03</td>
<td>SOLAR_BR_A03 &amp; WIND_VE_A03 &amp; WIND_VE_A04 &amp; WIND_VE_A02 &amp; WIND_BR_A03</td>
</tr>
<tr>
<td>WIND_VE_A03 &amp; WIND_BR_A03 &amp; WIND_VE_A03 &amp; WIND_VE_A04 &amp; WIND_VE_A02 &amp; WIND_BR_A03</td>
<td>SOLAR_BR_A01 &amp; WIND_VE_A03 &amp; WIND_VE_A04 &amp; WIND_VE_A02 &amp; WIND_BR_A03</td>
<td>SOLAR_BR_A03 &amp; WIND_VE_A03 &amp; WIND_VE_A04 &amp; WIND_VE_A02 &amp; WIND_BR_A03</td>
</tr>
<tr>
<td>SOLAR_ES_A01 &amp; WIND_BR_A01 &amp; WIND_VE_A03 &amp; WIND_VE_A04 &amp; WIND_VE_A02 &amp; WIND_BR_A03</td>
<td>SOLAR_BR_A01 &amp; WIND_VE_A03 &amp; WIND_VE_A04 &amp; WIND_VE_A02 &amp; WIND_BR_A03</td>
<td>SOLAR_BR_A03 &amp; WIND_VE_A03 &amp; WIND_VE_A04 &amp; WIND_VE_A02 &amp; WIND_BR_A03</td>
</tr>
<tr>
<td>WIND_AR_A01 &amp; SOLAR_ES_A01 &amp; WIND_VE_A03 &amp; WIND_VE_A04 &amp; WIND_VE_A02 &amp; WIND_BR_A03</td>
<td>SOLAR_BR_A01 &amp; WIND_VE_A03 &amp; WIND_VE_A04 &amp; WIND_VE_A02 &amp; WIND_BR_A03</td>
<td>SOLAR_BR_A03 &amp; WIND_VE_A03 &amp; WIND_VE_A04 &amp; WIND_VE_A02 &amp; WIND_BR_A03</td>
</tr>
<tr>
<td>WIND_VE_A03 &amp; WIND_VE_A04 &amp; WIND_VE_A02 &amp; WIND_BR_A03</td>
<td>SOLAR_BR_A01 &amp; WIND_VE_A03 &amp; WIND_VE_A04 &amp; WIND_VE_A02 &amp; WIND_BR_A03</td>
<td>SOLAR_BR_A03 &amp; WIND_VE_A03 &amp; WIND_VE_A04 &amp; WIND_VE_A02 &amp; WIND_BR_A03</td>
</tr>
<tr>
<td>SOLAR_ES_A01 &amp; WIND_VE_A03 &amp; WIND_VE_A04 &amp; WIND_VE_A02 &amp; WIND_BR_A03</td>
<td>SOLAR_BR_A01 &amp; WIND_VE_A03 &amp; WIND_VE_A04 &amp; WIND_VE_A02 &amp; WIND_BR_A03</td>
<td>SOLAR_BR_A03 &amp; WIND_VE_A03 &amp; WIND_VE_A04 &amp; WIND_VE_A02 &amp; WIND_BR_A03</td>
</tr>
<tr>
<td>WIND_VE_A03 &amp; WIND_VE_A04 &amp; WIND_VE_A02 &amp; WIND_BR_A03</td>
<td>SOLAR_BR_A01 &amp; WIND_VE_A03 &amp; WIND_VE_A04 &amp; WIND_VE_A02 &amp; WIND_BR_A03</td>
<td>SOLAR_BR_A03 &amp; WIND_VE_A03 &amp; WIND_VE_A04 &amp; WIND_VE_A02 &amp; WIND_BR_A03</td>
</tr>
<tr>
<td>WIND_VE_A03 &amp; WIND_VE_A04 &amp; WIND_VE_A02 &amp; WIND_BR_A03</td>
<td>SOLAR_BR_A01 &amp; WIND_VE_A03 &amp; WIND_VE_A04 &amp; WIND_VE_A02 &amp; WIND_BR_A03</td>
<td>SOLAR_BR_A03 &amp; WIND_VE_A03 &amp; WIND_VE_A04 &amp; WIND_VE_A02 &amp; WIND_BR_A03</td>
</tr>
</tbody>
</table>

Decrement (the correlation factor became more positive than 5%)
Discussion

Climate variables such as solar radiation and wind speed are important factors that influence renewable energy availability; thus, changes in these variables would impact the power generation and the complementarity between the hotspots analysed.

In the behaviour analysis of the wind and solar resources under the RCP4.5 and RCP8.5 scenarios, the impact of global climate change is more prominent in wind resources; this impact is greater in the RCP 8.5 scenario than the RCP 4.5 scenario. The data show a tendency for higher wind speeds in LA from 2040, especially in the Caribbean Region: WIND_VE_A03, WIND_SU_A01, WIND_CO_A02 and WIND_BR_A01. In some areas, like WIND_CO_A02 and WIND_VE_A01, the moving average in the final period (2071-2100) reaches values up to 44.03% and 42.80% higher than the historical mean. For both scenarios, RCP 4.5 and RCP 8.5, the solar resource of the hotspots did not show a significant variation in the average irradiation during the period of analysis.

As mentioned in this study, the RCP 4.5 is a scenario of intermediate mitigation, with a lower concentration of greenhouse gases in the atmosphere than the RCP 8.5 scenario. The RCP8.5 is the most pessimistic scenario, with more radiative forcing per square meter. Therefore, a lower impact was expected on the historical complementarity values of the analysed regions, due to climate change, in the RCP 4.5 scenario, and as presumed, for the whole period of analysis, the RCP4.5 scenario presents favourable results for the complementarities of the most pairs of regions. For the period of 2010 – 2040, 84% of the cases show no change or even improve their complementarity. For 2041 – 2070 and 2071-2100 the numbers were 78% and 73%, respectively. This means that for the last period of the projection only five pairs of hotspots had their complementarities negatively impacted (WIND_VE_A03 & WIND_BR_A03, SOLAR_BR_A03 & WIND_BR_A01, SOLAR_ES_A01 & WIND_AR_A01, SOLAR_VE_A03 & WIND_EC_A01, WIND_SU_A01 & WIND_BR_A04).

In this study the RCP8.5 scenario shows high impacts on the historical complementarities in the last period of the projection (2041-2070). 85% of the cases analysed show a decrease in the seasonal complementarities. For the period of 2040-2070, the decrease was in 17% of cases and 16% in the period of 2010-2040. Additionally, in the RCP8.5 scenario there were two special cases whose complementarities change to a positive correlation (SOLAR_BR_A03 & WIND_BR_A01 and WIND_PE_A01 & WIND_CO_A02) the first one in the period of 2071-2100 and the second one in the period of 2010-2040. It happens because the intra-annual behaviour of the resources for WIND_BR_A01 and WIND_CO_A02 undergo a strong variation.

The results of this study show strong negative impacts on the complementarities in the projection of the last analysed period. However, it is possible to see the results of both scenarios as an incentive for renewable energy investment in LA since, as far as this study can indicate, global climate change should not have a severe impact in the complementarity of most of the current potential areas to be integrated, until 2070.

Therefore, investors and energy planners should carefully evaluate the expansion of wind and solar power in those hotspots, especially if these areas are expected to benefit from the current complementarity by planning a future integration. Despite these cases, the study shows that climate change does not seem to be a barrier to the present and future development and integration of renewable energy sources in Latin America’s energy matrix.
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Background

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Results

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References

Appendices

References


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References


Appendices

7.1. Comparison between IDB database and GCMs simulation historical databases

This appendix presents the comparison between the equivalent year (seasonal pattern) of the IDB database and the equivalent year (seasonal pattern) of the GCMs historical simulation data for the areas that presented complementarity in the first report of this study.
7.2. Climate Change Impact on Energy Complementarities based on HadGEM2-ES model

Based on the climate projections for the IDB database, the energy complementarity was re-evaluated between the areas that had complementary in the first report of this study. This appendix shows the impact of climate change in the renewable energy complementarity between the hotspots analyzed for 3 different periods of time: 2010-2040, 2041-2070, 2071-2100 and for two scenarios: RCP 4.5 and RCP 8.5.

Climate Change Impact on Energy Complementarities based on HadGEM2-ES model and RCP 4.5 Scenario

- Historical
- 2010-2041
- 2041-2070
- 2071-2100
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Historical

2010–2041

2041–2070

2071–20100

Normalized data

R: −0.889

R: −0.93

R: −0.922

Month

Normalized data

R: −0.888

R: −0.909

R: −0.871

Month

Normalized data

R: −0.922

R: −0.962

R: −0.837

Month
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Historical

2010–2041

2041–2070

2071–2100

Normalized data

Month

Normalized data

Month

Normalized data

Month

Normalized data

Month

R: −0.875

R: −0.833

R: −0.865

R: −0.863

R: −0.911

R: −0.924

R: −0.94

R: −0.916
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Historical

2010–2041

Normalized data

R: −0.844

2010–2041

Normalized data

R: −0.925

2041–2070

Normalized data

R: −0.893

2071–2100

Normalized data

R: −0.862

2010–2041

Normalized data

R: −0.837

2041–2070

Normalized data

R: −0.897

2071–2100

Normalized data

R: −0.901

2010–2041

Normalized data

R: −0.903
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**Historical**

- **2010–2041**: Normalized data, $R = -0.835$
- **2041–2070**: Normalized data, $R = -0.642$
- **2071–2100**: Normalized data, $R = -0.451$

**2010–2041**

- Normalized data, $R = -0.71$

**Historical**

- **2010–2041**: Normalized data, $R = -0.832$
- **2041–2070**: Normalized data, $R = -0.522$
- **2071–2100**: Normalized data, $R = -0.455$

**2010–2041**

- Normalized data, $R = -0.508$
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Historical

2010–2041

2041–2070

2071–2100

2010–2041

2041–2070

2071–2100

Normalized data

Normalized data

Normalized data

Normalized data

Month

Month

Month

Month

Month

Month

Historical

Normalized data

Normalized data

Normalized data

Normalized data

Month

Month

Month

Month

Month

Month

R: −0.83

R: −0.905

R: −0.825

R: −0.839

R: −0.914

R: −0.89

R: −0.777

R: −0.777

SOLAR_BR_A03

WIND_VE_A03

SOLAR_BR_A03

WIND_VE_A03

SOLAR_BR_A03

WIND_VE_A03

SOLAR_BR_A03

WIND_VE_A03

SOLAR_VE_A03

WIND_EC_A01

SOLAR_VE_A03

WIND_EC_A01

SOLAR_VE_A03

WIND_EC_A01

SOLAR_VE_A03

WIND_EC_A01

SOLAR_VE_A03

WIND_EC_A01

SOLAR_VE_A03

WIND_EC_A01

SOLAR_VE_A03

WIND_EC_A01

SOLAR_VE_A03

WIND_EC_A01
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REPORT II

Historical

2010–2041

Normalized data

R: −0.802

2041–2070

Normalized data

R: −0.873

2071–2100

Normalized data

R: −0.877

WIND_BR_A01

WIND_AR_A01

2010–2041

Normalized data

R: −0.953

2041–2070

Normalized data

R: −0.801

2071–2100

Normalized data

R: −0.891

WIND_PE_A01

WIND_CO_A02

2010–2041

Normalized data

R: −0.874

2041–2070

Normalized data

R: −0.877

2071–2100

Normalized data

R: −0.849

WIND_PE_A01

WIND_CO_A02
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Historical

2010–2041

2041–2070

2071–2100

Normalized data

R: −0.802

R: −0.801

R: −0.873

Normalized data

R: −0.953

R: −0.877

Normalized data

R: −0.793

Normalized data

R: −0.877

Normalized data

R: −0.849

Month

Month

Month

Month

Normalized data

Normalized data

Normalized data

Normalized data
Climate Change Impact on Energy Complementarities based on HadGEM2-ES model and RCP 8.5 Scenario
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Historical

2010–2041

2041–2070

2071–2100

2010–2041

2041–2070

2071–2100
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7.3. Trend of the Climate Projection for Wind and Solar Resources based on HadGEM2-ES Model

This appendix presents the trend of the climate projection for wind and solar resources, of the selected cases, based on HadGEM2-ES Model simulation results for the RCP 4.5 and RCP 8.4 scenarios.
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**Appendices**

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**WIND_CO_A02**

Moving Average
- RCP 8.5
- RCP 4.5
- Historic

**WIND_PE_A01**

Moving Average
- RCP 8.5
- RCP 4.5
- Historic

**WIND_EC_A01**

Moving Average
- RCP 8.5
- RCP 4.5
- Historic

**WIND_SU_A01**

Moving Average
- RCP 8.5
- RCP 4.5
- Historic
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