The impact of climate change on wind and solar resources in southern Africa*

Charles Fant, C. Adam Schloesser and Kenneth Strzepek

*Reprinted with permission from
Applied Energy 161, online first (doi: 10.1016/j.apenergy.2015.03.042)
©2015 the authors
The MIT Joint Program on the Science and Policy of Global Change combines cutting-edge scientific research with independent policy analysis to provide a solid foundation for the public and private decisions needed to mitigate and adapt to unavoidable global environmental changes. Being data-driven, the Program uses extensive Earth system and economic data and models to produce quantitative analysis and predictions of the risks of climate change and the challenges of limiting human influence on the environment—essential knowledge for the international dialogue toward a global response to climate change.

To this end, the Program brings together an interdisciplinary group from two established MIT research centers: the Center for Global Change Science (CGCS) and the Center for Energy and Environmental Policy Research (CEEPR). These two centers—along with collaborators from the Marine Biology Laboratory (MBL) at Woods Hole and short- and long-term visitors—provide the united vision needed to solve global challenges.

At the heart of much of the Program's work lies MIT's Integrated Global System Model. Through this integrated model, the Program seeks to: discover new interactions among natural and human climate system components; objectively assess uncertainty in economic and climate projections; critically and quantitatively analyze environmental management and policy proposals; understand complex connections among the many forces that will shape our future; and improve methods to model, monitor and verify greenhouse gas emissions and climatic impacts.

This reprint is one of a series intended to communicate research results and improve public understanding of global environment and energy challenges, thereby contributing to informed debate about climate change and the economic and social implications of policy alternatives.

Ronald G. Prinn and John M. Reilly,
Program Co-Directors

For more information, contact the Program office:
MIT Joint Program on the Science and Policy of Global Change

Postal Address:
Massachusetts Institute of Technology
77 Massachusetts Avenue, E19-411
Cambridge, MA 02139 (USA)

Location:
Building E19, Room 411
400 Main Street, Cambridge

Access:
Tel: (617) 253-7492
Fax: (617) 253-9845
Email: globalchange@mit.edu
Website: http://globalchange.mit.edu/
The impact of climate change on wind and solar resources in southern Africa

Charles Fant *, C. Adam Schlosser, Kenneth Strzepek

MIT Joint Program for the Science and Policy of Global Change, Cambridge, MA, United States

HIGHLIGHTS

• We develop a risk-based assessment of climate change impacts on wind and solar resources.
• We compare results of two GHG mitigation policies in southern Africa.
• We find a low probability of significant changes for both wind and solar.
• The effects of mitigation are also mild, although they vary regionally.

ARTICLE INFO

Article history:
Received 13 November 2014
Received in revised form 5 March 2015
Accepted 6 March 2015
Available online 8 April 2015

Keywords:
Climate change
Wind energy
Solar energy
Southern Africa
Renewable energy

ABSTRACT

The mitigation of potential climate change while sustaining energy resources requires global attention and cooperation. Among the numerous strategies to reduce Green House Gas (GHG) emissions is to decommission carbon intensive electricity production while increase the deployment of renewable energy technologies – such as wind and solar power generation. Yet the generation capacity, availability, and intermittency of these renewable energy sources are strongly climate dependent – and may also shift due to unavoidable human-induced change. In this study, we present a method, based on previous studies, that estimates the risk of climate-change on wind and solar resource potential. The assessment combines the risk-based climate projections from the Integrated Global Systems Model (IGSM), which considers emissions and global climate sensitivity uncertainty, with more regionally detailed climate information from 8 GCMs available from the Coupled Model Intercomparison Project phase 3 (CMIP-3). Southern Africa, specifically those in the Southern African Development Countries (SADC), is used as a case study. We find a median change close to zero by 2050 in the long-term mean of both wind speed and Global Horizontal Irradiance (GHI), both used as indicators of changes in electricity production potential. Although the extreme possibilities range from about –15% to +15% change, these are associated with low probability. The most prominent effect of a modest climate mitigation policy is seen in the doubled likelihood of the mode of the distribution of wind power change. This increased likelihood is made at the expense of decreased likelihood in the large changes of the distribution, but these trade-offs with the more extreme likelihoods are not symmetric with respect to the modal change.

1. Introduction

The fundamental goal of any mitigation strategy to avoid the risk of climate change is a push towards lower Greenhouse Gas (GHG) emissions. However, the most promising energy generation sources that are essentially without emissions are typically climate dependent, which is especially the case for renewable energy resources such as wind and solar. As evidence from the Intergovernmental Panel on Climate Change [1] indicates that future climate will begin to behave less like past climates in the coming decades, 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. Southern Africa provides an interesting case study for this analysis, specifically the Southern Africa Development Countries (SADC), which includes the Democratic Republic of Congo, Tanzania, and all countries south of these two. Energy demand in this region of the world is rising quickly, with more than 12% in Mozambique and more than 10% in Zimbabwe, as observed in the last couple of years, for example [2].
Of the countries in this region, South Africa has shown the most interest in wind and solar technology investment. With 80% of the electricity capacity of the Southern Africa Power Pool [3], South Africa is one of the most carbon-intensive countries in the world [4]. Economic growth has been driven largely by the abundance of local coal resources, which currently satisfies about 77% of South Africa’s primary energy needs [5]. The accessibility of coal has resulted in a dependence on low-cost coal-fired electricity, energy intensive mining, and heavy industry [6]. Regardless, the South African government aims to reduce greenhouse gas emissions significantly, hoping to cut down on emissions by 42% by 2025 compared to a business-as-usual scenario [7], and the Department of Energy in South Africa plans to achieve 30% clean energy by 2025 [5]. In order to satisfy these goals, enormous changes in infrastructure must take place. One essential change in infrastructure is a move from coal-fired electricity to electricity generated from renewable sources—namely, biofuels, wind, solar, and imported hydropower. The major players in the electricity sector of South Africa are Eskom and the Department of Energy. Eskom generates approximately 95% of the electricity used in South Africa and 45% of the electricity used in Africa, and was converted from private to public in 2002 [8]. With stakes in the Cohora Bassa hydroelectric scheme in Mozambique, South Africa can import 1400 MW of firm energy, plus an additional 300 MW of non-firm energy [9]. Although renewable sources are occasionally used for rural areas that cannot feasibly connect to the national grid, commercially viable renewable energy capacity is not yet exploited on a large scale. Domestic hydropower capacity is small compared to other sources, less than 2% of current energy production, and has been almost fully developed [4].

There are few operational wind power plants in South Africa. Sere Wind Farm, to be among the largest wind farms, would be built near the city of Vredendal in the Western Cape by Eskom [10]. There has also been interest in South Africa to build large-scale PV and CSP to exploit its solar resource. Winkler [11] found that CSP is the most affordable renewable energy option for decreasing emissions in South Africa. Although there are no existing large-scale CSP plants in southern Africa, the South African electricity utility, Eskom, has recently invested in planning a 100 MW CSP plant in the Northern Cape near the city of Upington [8], and the South African government is promoting a 5000 MW solar park in the Northern Cape [12].

The implications of possible changes in usable wind and solar potential must be well understood for future planning purposes. Wind speed and cloudiness are strongly influenced by local temperature gradients as well as large-scale climate oscillations such as the El Nino Southern Oscillation (ENSO) and Madden-Julian Oscillation (MJO), which could behave differently in the future [13]. Meehl et al. [14] report that peak wind speeds will likely increase with increasing temperatures, and Hazeleger [15] suggests that the trade winds in particular are likely to change. Land surface changes can affect local cloudiness and could be amplified in urban areas [16], but making connections between climate change and changes in solar irradiation is a complicated matter [1]. In fact, understanding the impacts of climate change on both aerosols in the atmosphere and boundary layer wind speed are problematic because of the spatial scale of current General Circulation Models (GCMs). Studies have been begun to elucidate the impact of climate change on wind and solar parameters, but the subject is less studied than the impacts on biophysical sectors, e.g., agriculture.

1.1. Wind speed and solar irradiation in a General Circulation Model

A general concern regarding GCM outputs, in particular with any plausible future of renewable resource availability they may project, are the inherent uncertainties of climate modeling and the fidelity of their solutions. The full spectrum of this concern is outside the scope of this study. Rather, in order to assess the appropriate use of GCM output within the context of our study, we must recognize how wind and solar variables are represented. In a GCM, wind speed is explicitly resolved as an average over a finite volume (typically a cube) in space. In addition, some GCMs provide wind speed output at 10 m, an estimation derived from the wind speed values of the atmospheric layer closest to the surface. Vertical layers in a GCM are typically discretized with respect to air pressure, meaning that the layers’ altitude change in space and time. These layers are also unevenly distributed so that a finer resolution is achieved near the surface. In a typical GCM, the atmosphere is modeled with about 10–20 layers reaching to about 30 km. GCMs also represent the climate at a coarse horizontal resolution of about 250–600 km [17]. The problem with dividing the atmosphere into large cubes is that atmospheric processes occur at smaller scales. These relatively large finite volumes within GCMs are not ideal for modeling changes in smaller-scale winds (i.e. at the spatial extent of wind farms), which is highly dependent on the effects of elevation, surface roughness, and convection. Clouds and other aerosols can also change at smaller scales than a typical GCM grid. Cloud feedbacks in particular are considered the highest uncertainty in current GCM practice [18]. Cloud cover fraction output is usually estimated based on relative humidity values in each GCM cube. These small-scale processes must be represented as a function of the larger scale variables that are explicitly resolved at the GCM grid or finite volume – otherwise referred to as a “parameterization”. For studies that consider the large-scale atmospheric processes and their potential impact and interaction with “sub-grid” processes, parameterizations are an integral part of GCM projections that assess the potential of future changes in the climate system [18]. For all of these reasons listed, GCMs impart substantial uncertainties in resolving wind and solar variables. Although, in spite of the shortcomings of the GCMs, these models are the most well-trusted future projections available of the global climate—of which wind and solar are integral processes—and include state-of-the-art techniques in the field of climate science.

1.2. Previous attempts to characterize the future wind and solar state

In the past, climate change impact studies have typically involved one of two approaches: (i) a climate sensitivity analysis using a wide, unguided range of future climate possibilities; or (ii) use of select climate model output, typically Global Circulation Models (GCMs) from the Intergovernmental Panel on Climate Change (IPCC) Fourth Assessment Report (AR4) models. The output of these models is applied directly in a climate change impact-modeling framework to assess the impacts of climate change, resulting in a limited set of future scenarios. Research on the climate change impact on wind and solar resources follows a similar pattern, although recently there has been more activity within the latter of these two methodologies. Pryor et al. [19] attempted to estimate changes in the mean and upper percentile of wind speed in northern Europe. They used daily output from ten GCMs from the AR4 scenarios, fitting a regression model that predicts Weibull distribution parameters from station data. The model was calibrated using mean and standard deviation of 500 hPa relative vorticity and mean of daily sea-level-reduced pressure gradients from the historical GCM runs. Then, using future outputs of the predictors, they provide 10 possible futures of both the wind speed and wind power state, predicting the mean and 90th percentile of each. They found that there was not much
agreement between the GCMs, and no confident conclusion could be made about changes in wind characteristics by 2050 for the wind stations used. Looking further in the future, their study suggests that mean and 90th percentile wind speeds will decrease slightly by 2100. Sailor et al. [20] studied possible changes to wind speed and wind power over the northwestern United States. They used results from two GCMs under two of the IPCC AR4 scenarios. They found that the historical results from the GCMs did not match weather station measurements in the area. Applying a statistical downscaling technique to the raw GCM output, they found that the agreement improved. Overall, their study indicates that summertime winds will decrease by 5–10% in the area, and winter winds will either slightly increase or stay the same. Then, using typical hub heights and a common turbine power curve, they found that the power produced in the summer could decrease by about 40%; although it should be noted that this is a worst case value, estimated under the GCM projection uncertainties discussed previously. Pryor et al. [21] used a suite of thirteen simulations from a combination of four Regional Climate Models (RCMs) nested in reanalysis data and four global climate models. These simulations were compared to independent observations and the North American Regional Reanalysis (NARR) over the contiguous United States. The RCMs were found to exhibit some skill in reproducing historical wind patterns, and the RCM architecture seems to be the primary cause of variance between models rather than the lateral boundary conditions. The study then estimated changes in wind statistics averaged over 2041–2060. Some agreement between models was found that indicated intense wind speeds are likely to decrease, especially in the western U.S. by 2050. Seljøm et al. [22] links 10 GCM-scenario pairs to an RCM to estimate climate change effects on the Norwegian energy sector. Changes in wind, solar irradiation, and heating and cooling demand, among others, were estimated by interpolating the RCM results to 20 geographic locations: 7 for solar, and 13 for wind. The study found that while Global Horizontal Irradiance (GHI) and hydropower changes were significant in some of the GCM-senario projections, changes in wind were minor, with the maximum change for all locations and months around 4.8% by 2050. Fenger [23] came to a similar conclusion of changes in wind over Norway. Pan et al. [24] used a refined regional climate model to estimate seasonal changes in GHI simply by raising greenhouse gas concentrations in the regional model. A decreasing trend was found in the seasonal-mean of GHI of about 0–20% over the entire United States. This trend was most noticeable in the western U.S. during fall, winter, and spring.

There have been few studies that have looked at future changes in solar resource, likely due to the uncertainties in GCM cloud cover estimations discussed previously. Second, the studies that have estimated changes in wind speed have only found small long-term mean changes, the largest at 5–10%; although, Sailor et al. [20] does claim that small reductions in wind speed could result in large reductions in power produced. And third, these studies did not find much agreement between historical observations and GCM output, between the different GCMs, or the SRES scenario outputs of a single GCM.

In general, research on the impacts of climate change has followed a similar methodology. The past climate state is evaluated, and then information from climate models is applied. Next, climate change impact studies carefully apply a limited number of these scenarios in an intelligent way to understand the potential impacts of plausible future climate states. Since climate models are very computationally expensive, only a limited amount of scenarios can be effectively run to produce useful output, resulting in a paucity of possible future scenarios – particularly in the context of any comprehensive assessment of risk. In the vein, Schlosser et al. [25] presents a method to expand the set of CMIP-3 GCMs [26,27] developed near-surface temperature and precipitation projections at the zonal spatial scale for 400 scenarios representing economic and climate uncertainty. A Taylor expansion technique is then used to expand from the zonal level of detail in the longitudinal direction. This transformation requires the construction of climate-change pattern kernels, which vary through time as global temperature changes. The full ensemble of climate change projections is produced through the numerical hybridization of the IGSM zonal trends, with pattern kernels of regional climate change from 17 of the CMIP-3 models. Using this framework, 6800 climate projections are produced to construct “hybrid frequency distributions” (HFDs) for each of the five CO₂ emissions policy scenarios. To date the HFDs have been used to prescribe trends in meteorological variables (i.e. temperature and precipitation) that serve as atmospheric forcing to biophysical impact models (i.e. crop and hydrologic models) – and therefore develop risk-based assessments of change. In the next section, we describe a methodology that is similar to this risk-based approach, but has been adapted to our interest in wind and solar energy resource.

2. Data and method

First, a baseline needs to be established with which to compare the projected changes in climate. With the advancement of satellite measurements and data-assimilation model systems, global datasets that combine these are becoming more popular for areas with limited or unreliable set of historical data. For this study, the MERRA (Modern-Era Retrospective for Research and Analysis) reanalysis dataset will be used to represent the base climate for all solar and wind characteristics [28]. The MERRA dataset is attractive because it attempts to represent a balance between satellite, station, and modeled climate gridded globally at an hourly time-step from 1979 to 2009. Although there are certainly limitations to the reanalysis approach, MERRA improves on the representation of the hydrologic cycle and uses a large repository of conventional observations from various sources, as well as satellite radiance data. Fig. 1 shows the mean wind speed over southern Africa, calculated at 50 m using the log wind profile as described in

![Fig. 1. Geographic variation of mean wind speed (m/s) at 50 m over southern Africa.](image)
Gunturu and Schlosser. As shown, most of the onshore wind resource is in the southern and northeastern parts of the SADC region, with clusters of moderate wind speed in between. There is a large area of low wind speeds in the northwestern part of the map, comprised of the countries in the Congo River Basin and almost all of Angola. Fig. 2 shows the GHI at the surface. Most of the solar resource is in the southwest, surrounding Namibia and extending out to Zimbabwe, and in the northeast in Tanzania and Kenya.

The seasonal mean wind speed and GHI at select grids are shown in Table 1. The grid selected for wind speed is meant to represent the proposed Sere wind farm, previously discussed. Similarly, the GHI values were calculated from the grid containing the site of the proposed large CSP plant. As shown, the December–January–February (DJF) season has the potential for the most power produced, while the June–July–August (JJA) season has the least potential for both sources; although, the March–April–May (MAM) season has equally low potential for wind.

To understand changes in the future state of these resources, we explore the usefulness of a risk-based approach. Previous studies have used varying techniques to better understand the future state of wind and solar resource, using between 1 and 13 future scenarios. Given the recent advances in climate science provided through the HFD method, a larger pool of future scenarios can be generated, providing a more complete picture of the risk associated with climate change. However, a robust association needs to be established between the methods presented in Schlosser et al. and changes in both wind and solar resource.

A majority of the GCMs report both wind speed predictions at 10 m and GHI. Using these outputs, we have related global temperature rises with the gridded wind speed and GHI changes for each of the GCM and SRES where data are available from the CMIP-3 database. The seasonal mean was removed from each variable based on the mean of the first ten years. The evaluation of this method is described in the next section.

2.1. Statistical relationship

First, a Spearman rank correlation coefficient was calculated between mean global temperature and both wind speed and GHI for all seasons. We find that in the most extreme cases, the correlation is about 0.5 or −0.5. These values are fairly significant given that the predictor is a global parameter, and given the findings from the previous studies using the raw wind speed output from the GCMs. Fig. 3 shows the collective correlations for all GCMs with data for the A2 and B1 SRES. Here, we use the median correlation of all GCMs with at least 95% significance. We use white to represent grids where less than three GCMs have significant correlation. A qualitative observation from these maps is that the correlation values appear to be showing coherent patterns in various parts of the globe, indicating that the correlation is partly driven by large-scale relationships to the global temperature trend. We therefore use this association as a basis for our assessment, which is presented in the next section.

For this study, we also focus our attention at two locations in South Africa with characteristically different wind speed patterns and also contain large wind and solar farm installations. The first location is near the border of the Western Cape and Northern Cape. The second location is situated in the northern part of the Limpopo province. Looking at Fig. 3, although the highest correlation values are close to +/−0.5, the correlations are relatively low for these two locations for the majority of the GCM-SRES pairs – yet they are significant for the majority of the models, scenarios, and seasons. An additional aspect is that there is not a strong agreement between the SRESs for a given model, which is a compelling feature. If there was a strong agreement, we could assume that variance across model output is driven by differences in model structure. Instead, we find that the variance across model output must also be driven by the internal variability of the chaotic climate system that is modeled. This driver of uncertainty has been left for future research.

Given these considerations, our goal for this study is to quantitatively encompass the potential changes in wind and solar resource potential based on the implied relationships shown in Fig. 3. A locally weighted linear regression, as explained in Rajagopalan and Lall, is used as the statistical model to represent the relationship of global mean temperature to changes in both wind speed and GHI, although other statistical models could be used. We then estimate the changes in wind speed and GHI based on global temperature changes produced from the 400 IGSM scenarios. We use the CMIP-3 output data as a preliminary assessment, but we consider this method as quite flexible and there could be applied to the CMIP-5 data — as well any other GCM ensemble of projections of future climate as a result of an emissions or policy scenario.

3. Results

3.1. Results at selected sites

Due to the uncertainties of GCM output previously discussed, we restrict these results to projections in long-term mean seasonal changes in resource potential. Wind speed changes and changes in GHI are predicted to 2050 for southern Africa by averaging results over 11 years, from 2045 to 2055. As an example, wind speed
changes for the selected wind site and GHI changes for the selected solar site are discussed next. We focus on the summer and winter seasons, December through January (DJF) and June through August (JJA). DJF is the season with the highest wind potential in South Africa and JJA is the season with the highest demand for electricity [31]. We also present results for the Unconstrained Emissions (UCE) and Level 2 Stabilization (L2S) IGSM policy cases coupled with A2 SRES and B1, respectively. These SRESs are chosen because they best match the median radiative forcing of the corresponding policy [i.e., UCE and L2S] as shown in Prinn et al. [32]. This pairing of the SRES and the policy cases used in the HFD approach will be used for the remainder of this study. We use only the GCMs that have data for both A2 and B1, which results in 8 total GCMs and 3200 scenarios (400 x 8). As shown in Fig. 4, the changes in wind speed are relatively small, with mode and median of the anomalies close to zero and extremes from -1.5 to +1.5 m/s. Although, the modes of each distribution do suggest a slight increase in wind speed, the results suggest that modal wind speed changes would be insignificant by 2050 at the selected wind site for DJF and JJA seasons, with a small likelihood of either a positive or negative change of about 20%. The UCE policy case generally results in a lower likelihood of the modal result as well as a wider, i.e. more uncertain, distribution than the L2S. The exception is DJF wind speed increases. For the two plots of GHI, the mode for both seasons is slightly negative, especially in DJF, and close to the same for both policy cases. In the extreme results, changes range from about -30 to +30 W/m^2, which equates to approximately 10% of the mean.

3.2. Results over southern Africa

Fig. 5 shows the geographic variation of changes in wind speed for the DJF season over southern Africa. The 20th, 50th, and 80th percentiles are shown to represent the distribution of results over the 3200 scenarios. The top row presents the L2S policy case, and the bottom row, the UE policy case. For the most part, wind speed changes are small in southern Africa. The most extreme wind speed increases occur in the ocean, where the median change reaches about +0.6 m/s off the coast of South Africa. These increases do include the southern coast of South Africa, where wind potential is currently high. These same patterns emerge through all six maps. In general, although the differences in the results from the two policy cases are relatively small, the same pattern emerges—UE presents a wider range of possible wind speed changes, as shown in the 20th and 80th percentiles. Fig. 6 shows the wind speed changes for the JJA season. Here we see a slightly different pattern of changes, where southern South Africa shows decreases in wind speed in the median case, while the in Atlantic
Ocean off the coast of Namibia we see substantial increases in wind speed. There are also small increases in wind speed in Botswana. This pattern persists in both policy cases, with larger uncertainty in the UE case.

Fig. 4. Density distributions of projected wind speed changes (m/s; top row) for the selected wind site and GHI (W/m$^2$; bottom row) for the selected solar site for two seasons, December–January–February (DJF) and June–July–August (JJA), and two policies (L2S and UE).

Fig. 5. Geographic and scenario distribution of wind speed changes (m/s) for Dec–Jan–Feb. Subplots (a–c) show the 20th, 50th, and 80th, percentiles, respectively, for the Level 2 Stabilization (L2S) policy case and (d–f) show the same percentiles for the Unconstrained Emissions (UE) policy case.

Fig. 7 shows the geographic variation of changes in GHI for the DJF season and Fig. 8 for the JJA season. For the DJF season, the median result shows a predominance of increased GHI over inland areas, especially for UE. While for the JJA season, the median shows...
Fig. 6. Geographic and scenario distribution of wind speed changes (m/s) for Jun–Jul–Aug. Subplots (a–c) show the 20th, 50th, and 80th, percentiles, respectively, for the Level 2 Stabilization (L2S) policy case and (d–f) show the same percentiles for the Unconstrained Emissions (UE) policy case.

Fig. 7. Geographic and scenario distribution of GHI (W/m²) changes for Dec–Jan–Feb. Subplots (a–c) show the 20th, 50th, and 80th, percentiles, respectively, for the Level 2 Stabilization policy case and (d–f) show the same percentiles for the Unconstrained Emissions policy case.
a decrease in GHI over most of the region, except an area around Malawi, west along the equator, and the southwestern tip of South Africa. A spatial saturation of decreases-only and increases-only emerge in the 20th and 80th percentile maps, respectively. The strongest effect of the L2S scenario is seen in DJF, where the values – especially the local maxima and minima – in the 20th and 80th percentile maps are substantially reduced. This impact is not seen for the JJA season.

As discussed, there is much uncertainty in deriving these results, mostly from the GCMs themselves. This uncertainty is not only an important caveat when reaching these conclusions, but also appears to unfold in the results themselves by providing results that resemble a white noise signal or a classic error distribution, i.e., a relatively wide distribution with both median and mode close to zero. While we do notice patterns, as just described, we are unable to distinguish between the patterns that are results of error and the patterns that are robust future predictions.

4. Closing remarks

As a response to previous studies that have aimed to dissect GCM output from a select set of model results in order to understand the future state of wind and solar resource potential, we have shown 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 wind and solar parameter estimations, efficiently producing a portfolio of possible outcomes. The results resonate with previous findings—we find small that changes in wind and solar potential by 2050 are expected to be small. However, we also find a wide range to the distributional as well as regional results. These differences are a result of model-response disparity as well as the choice of emission scenario. The most salient distributional effect of these factors is that, for our selected location, the likelihood of a small change in windspeed is substantially increased under the mitigation scenario. Regionally speaking, we find non-negligible buffering effects, through climate mitigation, in the near quartile-value patterns (i.e. 20th and 80th percent) for summertime GHI changes.

Overall, these regional and distributional shifts as a result of mitigation efforts reflect the ability to avoid risks of more drastic changes in renewable energy supply. However, these effects are quite diverse and tied to particular seasons, regions and energy generation resources. Thus, more comprehensive assessments – beyond the scope of this more physically based exploration – are required that consider the net costs and benefits of scale and landscape to the generation technology deployed. Also, as noted, there is considerable inherent uncertainty in this analysis. We hope that further analysis will reveal a clearer distinction between the GCM output noise and discernable impacts on these renewable energy systems. Nevertheless, the results of this study indicate that, overall, the long-term mean wind and solar resource potential will – most likely (i.e. in the mode and median) – remain unchanged by 2050.
Acknowledgements

This study of the wind resource in southern Africa was funded by United Nations University – World Institute for Development Economic Research (UNU-WIDER). The authors gratefully acknowledge this as well as additional financial support for this work provided by the MIT Joint Program on the Science and Policy of Global Change through a consortium of industrial sponsors and Federal grants.

References


