Updated Climate Change Projections for eThekwini Municipality

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Climate Adaptation Services

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Summary

This report describes the main features of updated climate projections for eThekwini Municipality. Historical climate records as well as different climate scenarios based on the Representative Concentration Pathways (RCPs) 2.6 (1.5 degrees), 4.5 and 8.5 have been analysed. From these projections the following general conclusions can be drawn:

- Air temperature has been increasing over the past decades. Maximum air temperatures have increased stronger than mean and minimum air temperatures. Increases are also observed for temperature extremes such as tropical night occurrences and heat waves.
- These increasing trends are projected to continue in the coming decades (the analysis reaches up to 2050). Realizing the RCP2.6 scenario would lead to lowest increase and under RCP8.5 trends would continue more or less at the current level.
- Precipitation sums have been slightly decreasing over the past decades, in particular for the summer season. Precipitation extremes on the other hand have become more frequent and more intense.
- Precipitation projections for the future have high uncertainties. The future precipitation sums are hard to project, but it is likely precipitation extremes such as high rainfall events and drought occurrences increases further in frequency and intensity.

These climate projections are basis for a Climate Story Map developed for eThekwini Municipality.

1 Background

1.1 Project Background

The C40 Business Plan aims for all C40 cities to adopt an integrated and inclusive climate action plan to deliver low-carbon resilient development consistent with the 1.5˚C and adaptation objectives of the Paris Agreement. To help realize this aim, and support cities to prepare robust climate action planning, C40 established a Climate Action Planning Technical Assistance Programme.

The Climate Action Planning Technical Assistance Programme focuses on supporting a limited number of C40 cities to develop exemplar climate action plans, and mobilise political support to 1.5˚C across the C40 network. As part of this phase, C40 have also developed a 1.5˚C planning and assessment framework and a delivery framework for expanding support to all C40 cities for 1.5˚C climate action planning. The framework requires that climate actions are informed by a clear understanding of risks and hazards that a city is currently facing and is going to face in the context of a changing climate.

C40 is supporting a small set of pilot cities to develop and update their climate action planning (mitigation and adaptation) to ensure it meets 1.5°C Paris agreement level of ambition. The technical assistance will be city-led, with the city identifying those areas where technical assistance will make the most effective contribution to the development of their climate action plans. The eThekwini Municipality (City of Durban) in South Africa is one of the cities participating in the pilot.

Climate Adaptation Services and FutureWater are conducting this technical assistance, named “Climate Projections and Risk Assessment for eThekwini Municipality (Durban)”. This report briefly describes the work undertaken under part of the assignment: “Update climate projections”, or Identification of Climate Hazards (item 3.1 in Figure 1).

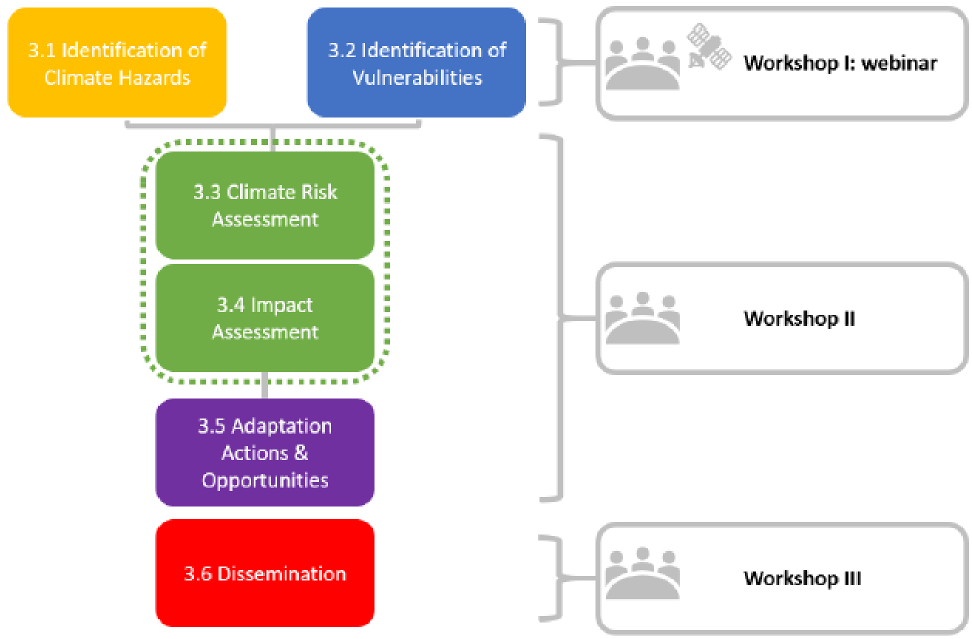


Figure 1: Project structure.

1.2 Climate change projections and climate modeling

1.2.1 Representative Concentration Pathways

Since the release of Intergovernmental Panel on Climate Change's fifth Assessment Report, four representative concentration pathways (RCPs) have been defined as a basis for long-term and near-term climate modeling experiments in the climate modeling community (van Vuuren et al. 2011). The four RCPs together span the range of radiative forcing values for the year 2100 as found in literature, from 2.6 to 8.5 Wm^{-2}. Climate modelers use the time series of future radiative forcing from the four RCPs for their climate modeling experiments to produce climate scenarios. The development of the RCPs allowed climate modelers to proceed with experiments in parallel to the development of emission and socio-economic scenarios (Moss et al. 2010). The four selected RCPs were considered to be representative of the literature, and included one mitigation scenario (RCP2.6), two medium stabilization scenarios (RCP4.5/RCP6) and one very high baseline emission scenario (RCP8.5) (van Vuuren et al. 2011).
Since the four RCPs are considered to be representative of radiative forcing that can be expected by 2100, each of them should theoretically be considered with equal probability to be included in climate change impact studies. However, in climate change impact studies there is usually a trade-off in how many RCPs and how many climate models can be included within the available time and resources, whilst at the same time having the ability of producing robust and reliable results.

Table 1: Description and visualization of the four representative concentration pathways (RCPs). Source: (van Vuuren et al. 2011)

RCP	Description
RCP8.5	Rising radiative forcing pathway leading to 8.5 Wm^2 (~1370 ppm CO_2eq) by 2100
RCP6	Stabilization without overshoot pathway to 6 Wm^2 (~850 ppm CO_2eq) at stabilization after 2100
RCP4.5	Stabilization without overshoot pathway to 4.5 Wm^2 (~650 ppm CO_2eq) at stabilization after 2100
RCP2.6	Peak in radiative forcing at ~3 Wm^2 (~490 ppm CO_2eq) before 2100 and then decline (the selected pathway declines to 2.6 Wm2 by 2100

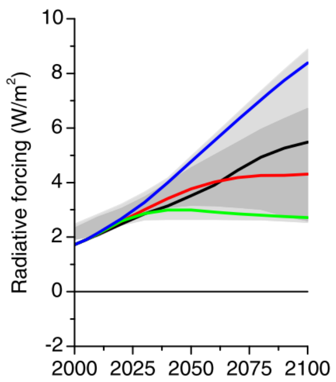


Figure 2: RCPs. blue: RCP8.5, black: RCP6, red: RCP4.5, green: RCP2.6. Source: (van Vuuren et al. 2011)

Between 1996 and the release of the IPCC's fifth assessment report in 2013 (IPCC 2013), the IPCC used a different set of future scenarios, combining main demographic, economic and technological driving forces with future greenhouse gas emissions. These scenarios were used in some of the literature cited in this thesis. An extensive description of the scenarios can be found in the IPCC's special report on emission scenarios (IPCC 2000).

1.2.2 Types of climate models

Climate is modeled at different spatial scales. General Circulation Models (GCMs) are used to simulate global climate and operate at spatial resolutions ranging from ~100 km^2 to ~250 km^2. Regional Climate Models (RCMs) can be used to simulate regional climate at a typical resolution of ~10-50 km. Climate change information is usually required at a higher spatial resolution since applications like hydrological models, forced by the data from GCMs or RCMs, operate at higher resolutions, down to several meters. The hydrological models used in the research described in this thesis operate at 1 km^2 spatial resolution.

The current state-of-the-art GCMs are organized in the fifth Coupled Model Intercomparison Project (CMIP5) archive (Taylor et al. 2012), which was used as a basis by the IPCC for the generation of its fifth Assessment Report. A similar effort to organize the output from RCMs is the CORDEX framework (Giorgi et al. 2009). The earlier CMIP3 (Meehl et al. 2007) archive is the main archive used for studies prior to the release of the CMIP5 archive.

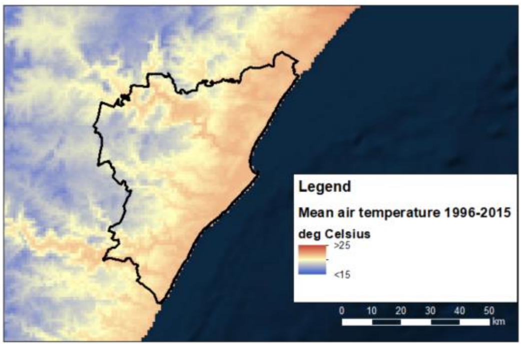
Section 2.2 describes which GCMs have been selected as basis for updated climate projections for eThekwini Municipality, and why these have been chosen.

2 Methodology

2.1 Historical reference climate

To analyse trends in the historical climate and to make future projections possible, a gridded historical reference climate dataset is required. The Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) dataset is a 30+ year rainfall dataset, developed for Africa (Funk et al. 2015). CHIRPS incorporates 0.05° (~5 km) resolution satellite imagery with in-situ station data to create gridded rainfall time series for trend analysis. The CHIRPS product is further downscaled to 1x1 km using the WorldClim 2 dataset (Fick and Hijmans 2017). This dataset provides a climatology at 1x1 km resolution. The monthly climatology fields are used to scale the daily CHIRPS precipitation fields to 1x1 km resolution within each 5x5 km grid cell. A period of 20 years spanning from 1 January 1996 to 31 December 2017 is selected. This period is covered at a daily time step.

For air temperature the WATCH Forcing Data ERA-Interim dataset is used (Weedon et al. 2014). This dataset combines reanalysis data from ERA-Interim (Dee et al. 2011) with station data from the GPCC dataset (Huffman et al. 1997). The data is downscaled to 1x1 km resolution using a high resolution Digital Elevation Model (DEM) and vertical temperature lapse rates. The processed dataset contains daily average, maximum and minimum air temperature at a daily time step, covering 1 January 1996 until 31 December 2016.



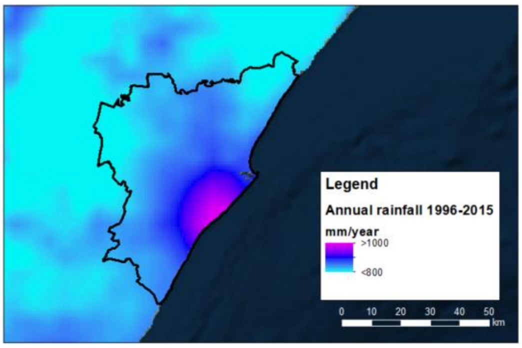


Figure 3: Mean air temperature and mean annual rainfall for 1996-2015, to illustrate the reference climate dataset.

2.2 Climate model selection

Climate change impact studies depend on projections of future climate provided by climate models (GCMs). The number of GCMs available for climate change projections is increasing rapidly. For example, the CMIP3 archive (Meehl et al. 2007), which was used for the 4th IPCC Assessment Report (IPCC 2007) contains outputs from 25 different GCMs, whereas the CMIP5 archive (Taylor et al. 2012), which was used for the 5th IPCC Assessment Report (IPCC 2013), contains outputs from 61 different GCMs. These GCMs often have multiple ensemble members resulting in an even larger number of available model runs.
Despite improvements in the CMIP5 models compared to CMIP3 in terms of process representation [e.g. *Blázquez and Nuñez*, 2013; *Sperber et al.*, 2013], uncertainty about the future climate remains large [e.g. *Knutti and Sedláček*, 2012], and locally even increases with the larger number of models available [e.g. *Joetzjer et al.*, 2013; *Lutz et al.*, 2013]. Considering the large number of available climate models and constraints in the available computational and

human resources, detailed climate change impact studies cannot include all projections. In practice, rather one climate model or a small ensemble of climate models is selected for the assessment. Despite the importance of using an ensemble that is representative for the region of interest and shows the full uncertainty range, the selection of models to be included in the ensemble is not straightforward, and can be based on multiple criteria.

Often climate models are selected based on their skill to simulate the present and near-past climate [e.g. *Biemans et al.*, 2013; *Pierce et al.*, 2009]. Here we refer to this approach as the past-performance approach. Another approach is the so-called envelope approach, where an ensemble of models covering a wide range of projections for one or more climatological variables of interest is selected from the pool of available models. This approach aims at covering all possible futures as projected by the entire pool of climate models. Some approaches consider only the changes in mean air temperature and total annual precipitation [e.g. *Immerzeel et al.*, 2013; *Sorg et al.*, 2014; *Warszawski et al.*, 2014], whereas other approaches consider more climatological variables using cluster analysis algorithms [e.g. *Cannon*, 2014; *Houle et al.*, 2012]. Another approach uses criteria for model independence to generate a representative selection of models from a larger ensemble, where the ensemble of selected models has characteristics that reflect the larger ensemble (Evans et al. 2013).

The major drawback of envelope-based approaches is that the models' skill to simulate climate are not considered, since all available climate model runs are considered to have equal plausibility and only changes in the annual means are criteria for selection. Besides, a large number of models needs to be considered, which may lead to less clear results and advice. On the other hand, selecting only models with a high skill in simulating present and past climate may lead to omission of possible futures. These two contrasting methods to select a climate model ensemble will result in different ensembles, with different mean projections and different uncertainties in the climate change projection.

The uncertainty originating from the spread in climate models' projections is considered to be a large source of uncertainty in climate change impact studies, e.g.: this uncertainty is often larger than model parameter uncertainties, uncertainty stemming from natural variability and structural uncertainties in hydrological models (Minville et al. 2008; Finger et al. 2012). Therefore, the selection of climate models is a crucial step when conducting a climate change impact study.

In this study the past-performance and envelope method are used both. Earlier research (Hughes et al. 2014) found that the MPI-ESM-LR climate model performed well for all areas included in their study for South Africa, when compared to actual past climate (Figure 4). Although no site at the East Coast is included in the study, the selected GCM scores high in all the areas over South Africa, in particular the different coastal areas. This provides confidence in the assumption that this GCM has high skill over the location of eThekwini Municipality too. This model was used for the RCP2.6, corresponding to a 1.5 °C global temperature increase scenario, and RCP4.5, the medium stabilization scenario.

Rainfall seasonality

Skill Rank	W Cape Coast				S Cape Coast		E Cape Coast	
	H10A	H10E	H10G	H10L	K90A	K90F	R20B	R20G
1	GISS	GISS	MPI	MRI	MPI	MPI	GFDL	MPI
2	MRI	CCCMA	MRI	GISS	GISS	GFDL	MPI	MRI
3	CCCMA	GFDL	CSIRO	CCCMA	GFDL	IPSL	MRI	GFDL
4	GFDL	IPSL	CCCMA	IPSL	CNRM	CNRM	CCCMA	GISS
5	MPI	MRI	CNRM	MPI	CSIRO	CCCMA	CSIRO	CSIRO
6	IPSL	CSIRO	GFDL	GFDL	MRI	GISS	IPSL	CCCMA
7	CSIRO	MPI	IPSL	CNRM	CCCMA	MRI	GISS	IPSL
8	CNRM	CNRM	MIUB	MIUB	IPSL	MIUB	CNRM	MIUB
9	MIUB	MIUB	GISS	CSIRO	MIUB	CSIRO	MIUB	CNRM

Coefficient of variation

Skill Rank	W Cape Coast				S Cape Coast		E Cape Coast	
	H10A	H10E	H10G	H10L	K90A	K90F	R20B	R20G
1	GISS	GISS	MPI	MRI	MPI	MPI	GFDL	MPI
2	MRI	CCCMA	MRI	GISS	GISS	GFDL	MPI	MRI
3	CCCMA	GFDL	CSIRO	CCCMA	GFDL	IPSL	MRI	GFDL
4	GFDL	IPSL	CCCMA	IPSL	CNRM	CNRM	CCCMA	GISS
5	MPI	MRI	CNRM	MPI	CSIRO	CCCMA	CSIRO	CSIRO
6	IPSL	CSIRO	GFDL	GFDL	MRI	GISS	IPSL	CCCMA
7	CSIRO	MPI	IPSL	CNRM	CCCMA	MRI	GISS	IPSL
8	CNRM	CNRM	MIUB	MIUB	IPSL	MIUB	CNRM	MIUB
9	MIUB	MIUB	GISS	CSIRO	MIUB	CSIRO	MIUB	CNRM

Figure 4: Table showing high skill for the MPI GCM (Hughes et al. 2014)**.**

For the higher end of the temperature projections (RCP8.5), two other climate models were selected (inmcm4 and CMCC-CMS), which together represent the full spectrum of possible future precipitation changes (i.e. a “wet” model and a “dry” model). These models are further referred to as RCP8.5 wet and RCP8.5 dry.

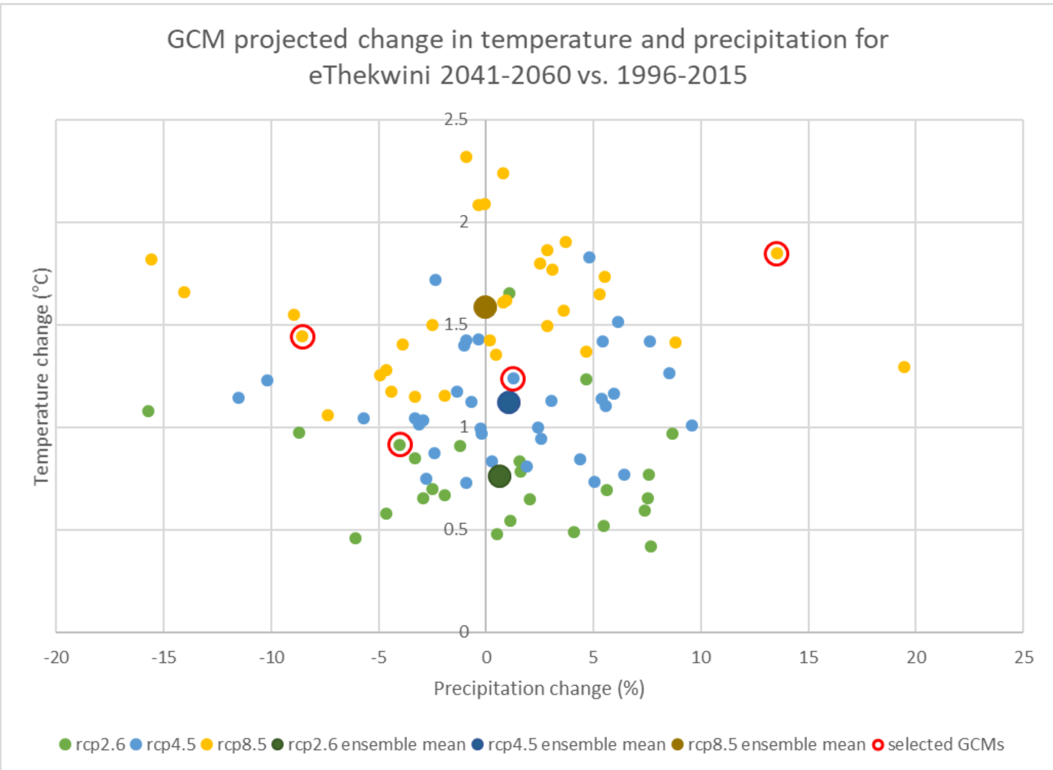


Figure 5: Full spectrum of climate model projections for eThekwini. Selected GCMs for this assignment are indicated by red circles.

2.3 Combining high resolution historical reference climate and future climate data

Because GCM data has a much coarser resolution compared to historical climate data (in this case 1x1 km), information from the higher resolution historical climate data is used to downscale data from the GCMs. The GCM data for the historical period (1996-2015) and the future period (2041-2060) are compared and analyzed for changes in a large set of climate indicators. Subsequently these changes are superimposed on the high-resolution historical climate dataset to obtain high resolution future climate and bias-correct for the biases between observations and climate model data. This well-established “delta change” (Arnell 1998) or perturbation method is widely applied.

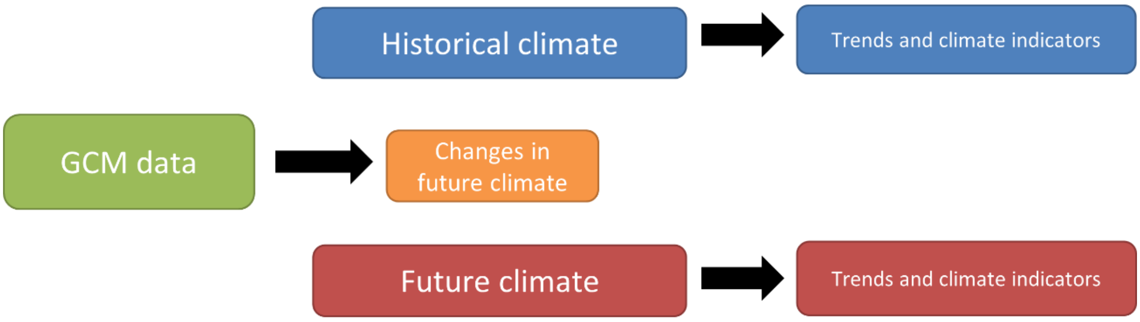
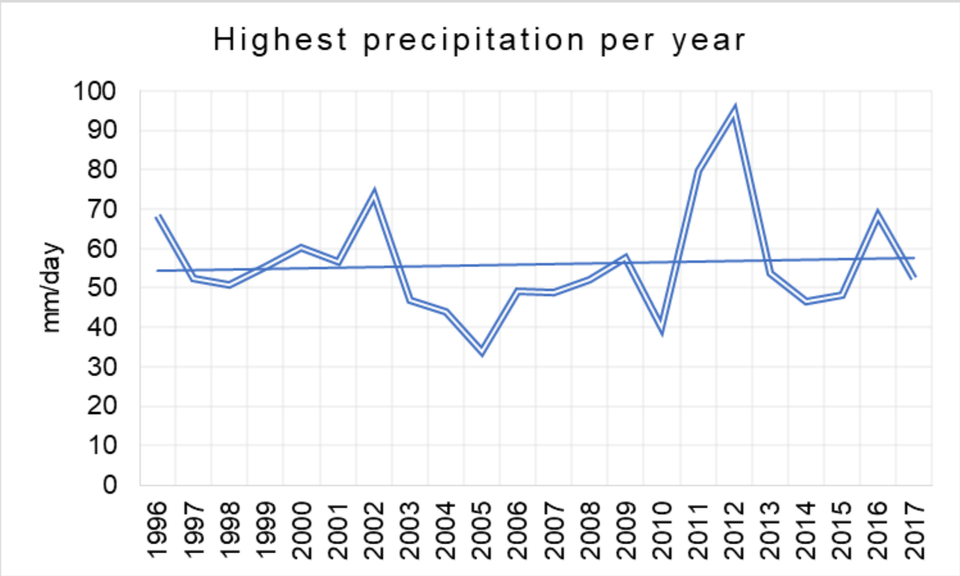


Figure 6: Schematic respresentation of combining historical data en GCM data.

This method assumes that the bias between observation and climate models is stationary in time (Dixon et al. 2016).

3 Historical climate trends

The analysis of the historical climate data provides insights in the climate's past development. The results shown here are partly presented in the Story Map as well. Analysis of precipitation shows a trend of annual sums which seems to become more erratic in the past 10-15 years. For the highest precipitation per year there is a slightly increasing trend, and the highest precipitation event was in the second half of the period (Figure 7). The annual precipitation sums are slightly decreasing and have become more erratic in the second half of the reference period (Figure 7).



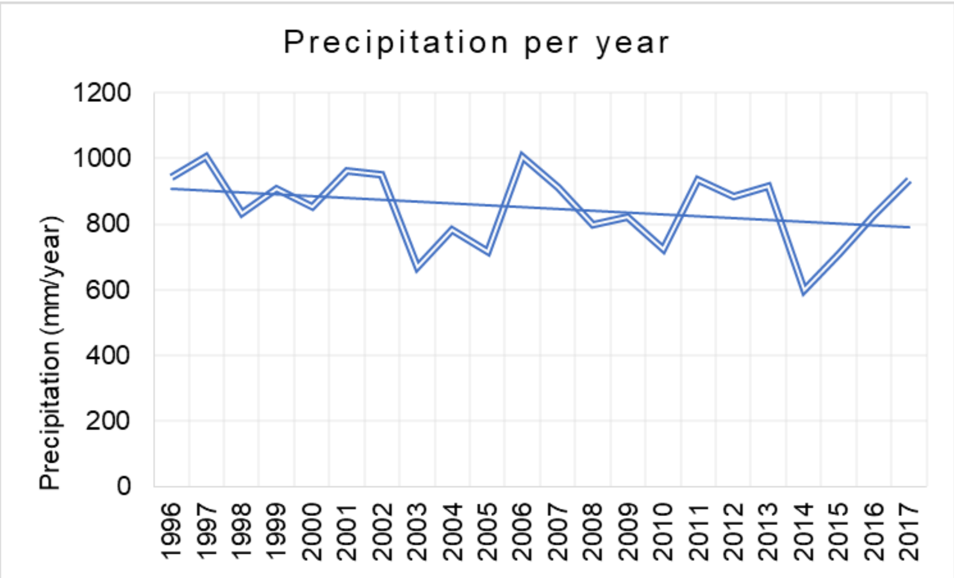


Figure 7: Annual maxima of daily precipitation sums (top) and time series of annual precipitation sums (bottom).

Looking at the precipitation trends per season reveals that the decreasing precipitation trend in Figure 7 is solely related to the summer months (December, January, February) (Figure 8). For spring and winter, no trend is visible, whereas a very slightly increasing trend is observed for autumn precipitation.

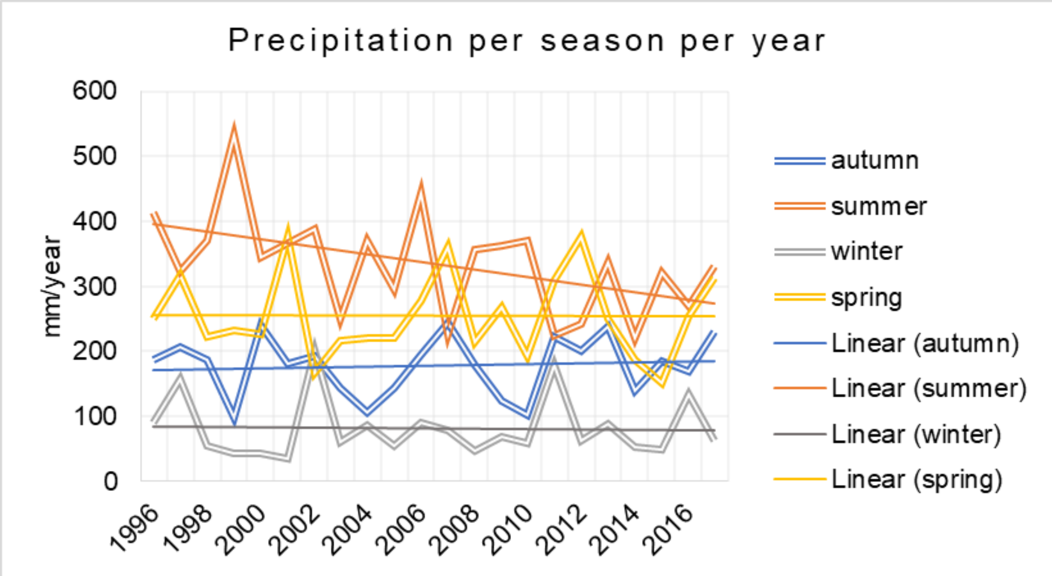


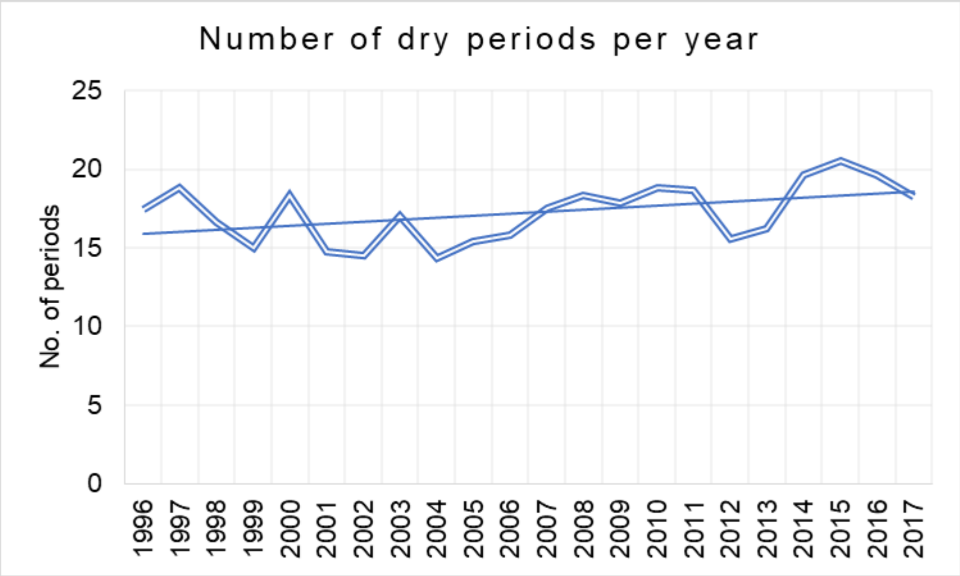
Figure 8: Precipitation sums per season per year.

The number of dry periods per year shows a clear increasing trend, for the first time exceeding 20 periods in 2015 (Figure 9). The length of the longest dry period per year is very erratic, and more erratic in the past 10 years, compared to the 10 years before (Figure 9). For example, between 2008 and 2017, years with a large number of dry days and years with a small number of dry days are alternating shortly after each other. During 1996-2006 years with many dry days and years with less dry days are more clustered.

Annual mean air temperature is on a constant rise during the past 20 years (Figure 10). During 1996-2016 the average temperature increased from 19.8 to 21.4 °C In particular the last 3-4 years temperature has been rising strongly (0.28 °C/year). Trends in mean, maximum and minimum air temperature for the four different seasons all show increasing trends (Figure 11). Striking is that the trend for maximum air temperature during summer, autumn and spring shows a stronger increase than during winter. In general the trends for the maximum air temperature are stronger increasing than for the mean air temperature and minimum air temperature.

The hottest observed summer day temperature per year shows a clear increasing trend over the reference period (Figure 12). In terms of the number of hot nights, which affect human health if the human body cannot cool down sufficiently after a hot day, in the second half of the reference period a threshold of 10 tropical night has been exceeded regularly, and a clear increasing trend is observed (Figure 12).

The number of heat waves per year has also been increasing gradually during 1996-2015. In this analysis a heat wave is defined as a period of at least 6 consecutive days with daily maximum temperature at least 5 degrees higher than the long-term average of the daily maximum temperature for that particular time period of the year. Years with one heat wave are common, but the number of years with more than one heat wave seems to be increasing (Figure 13).



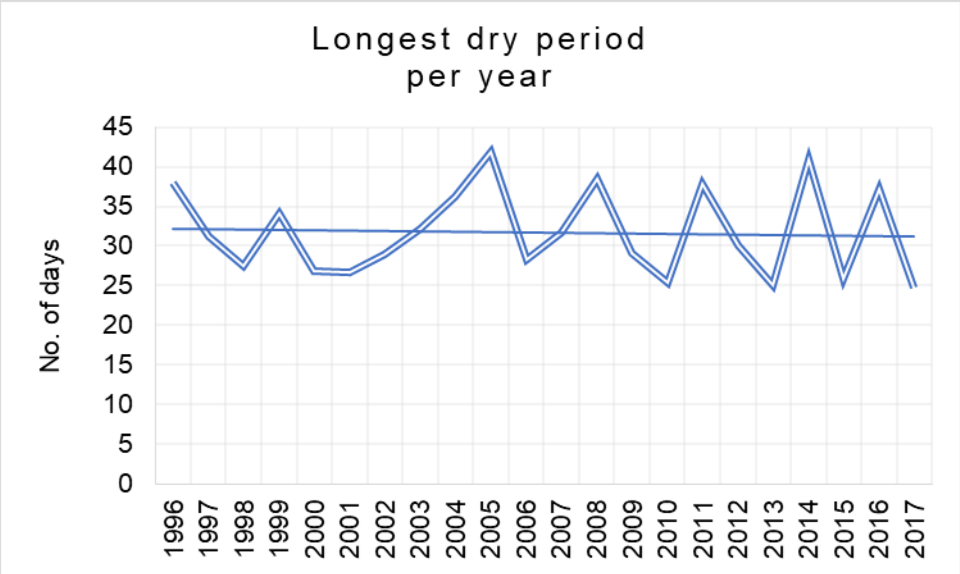


Figure 9: Number of dry periods per year and longest dry period per year. A dry period is defined as a period of minimum 5 days length with less than 1 mm of rainfall.

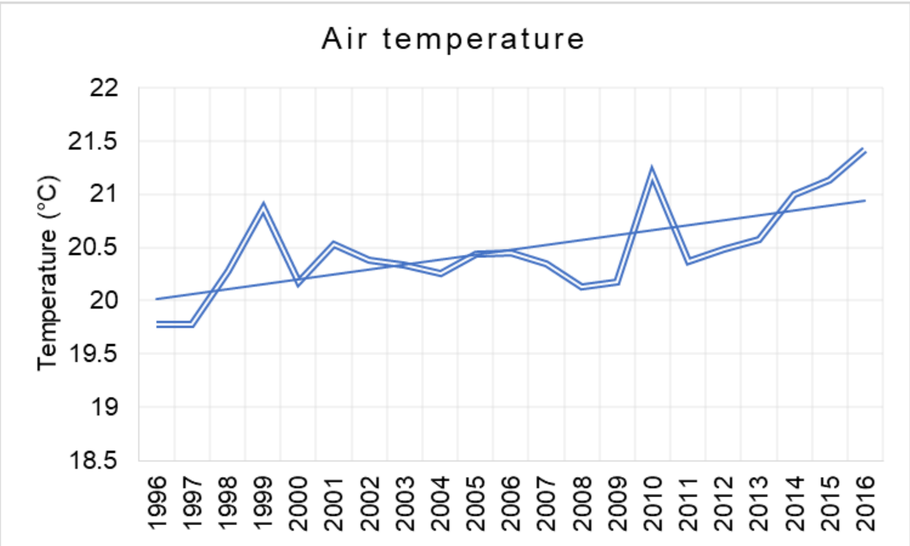


Figure 10: Annual mean air temperature time series.

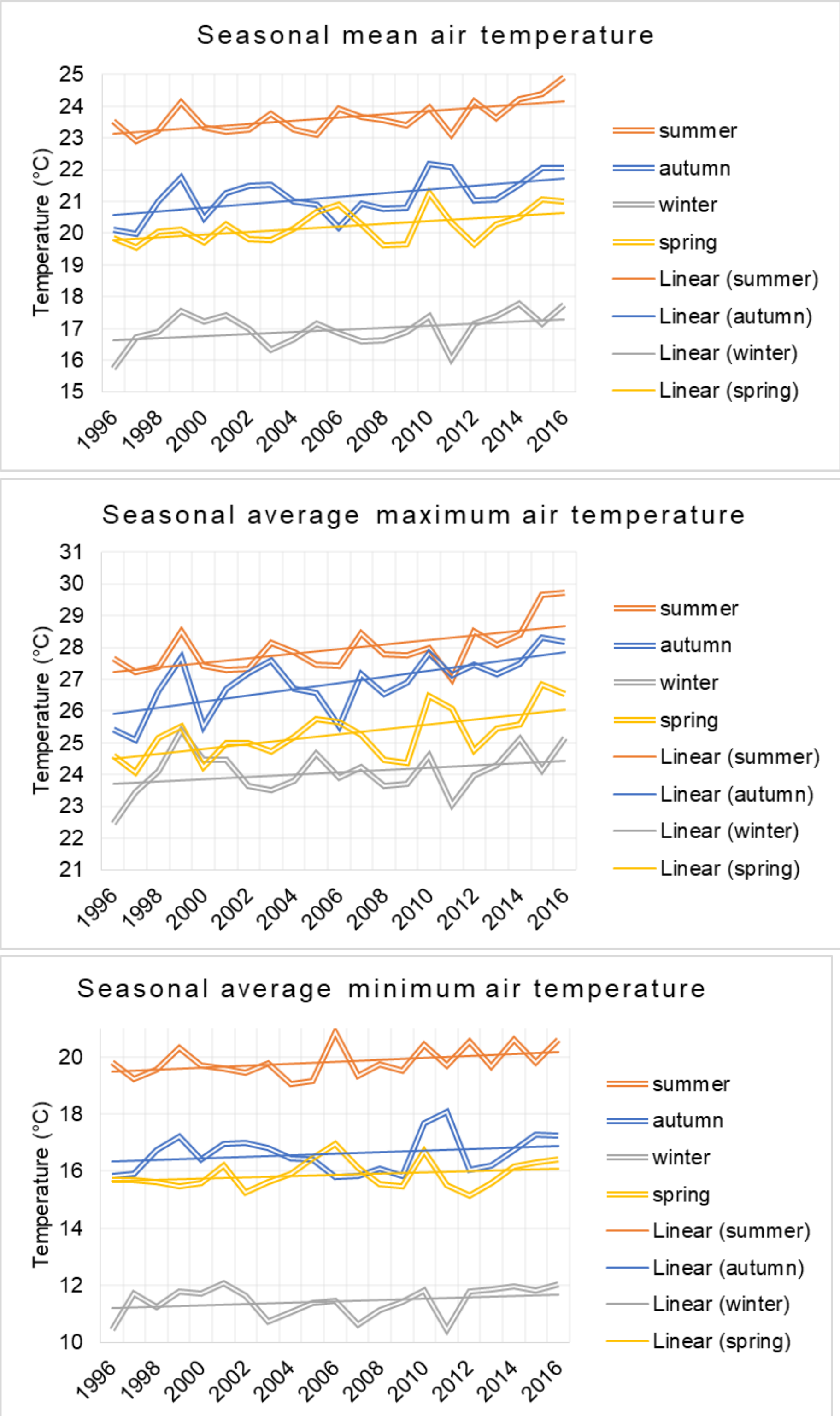
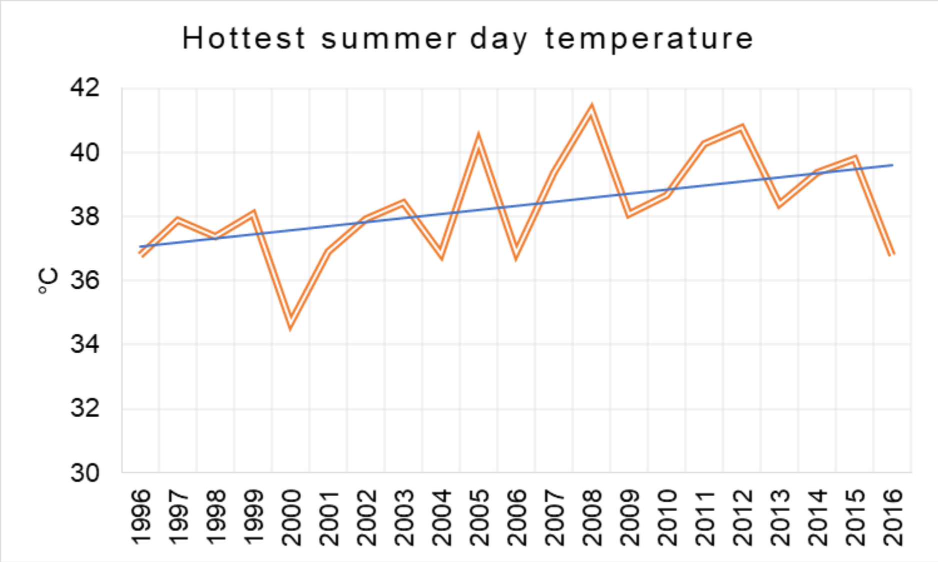


Figure 11: Time series of average annual mean, maximum and minimum temperature differentiated for four seasons.



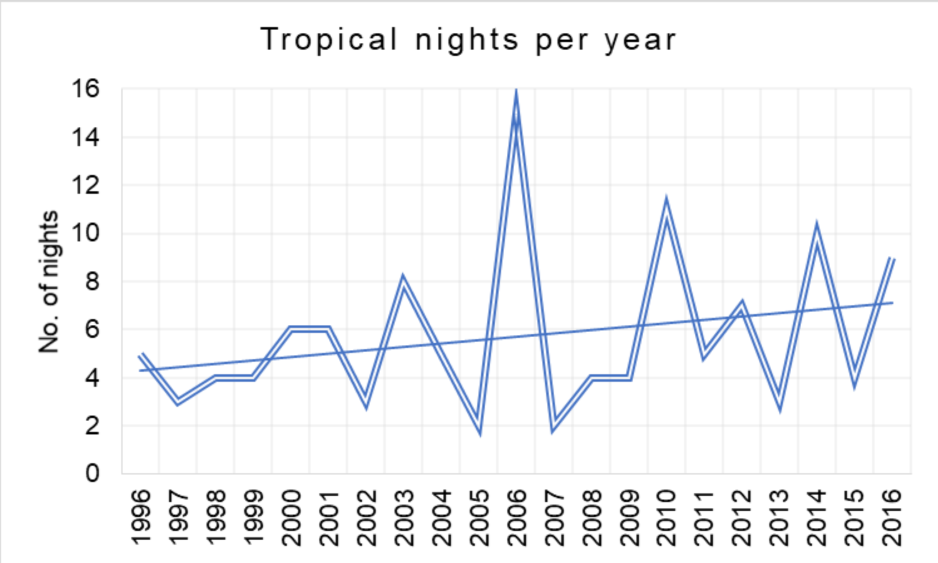


Figure 12: Hottest summer day temperature and number of tropical nights per year. A tropical night is defined as a night with minimum temperature above 23 °C.

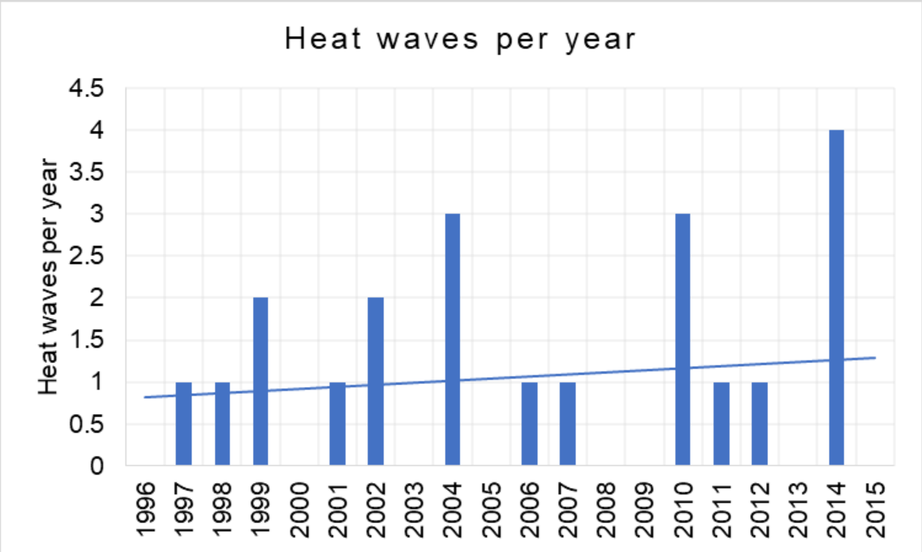
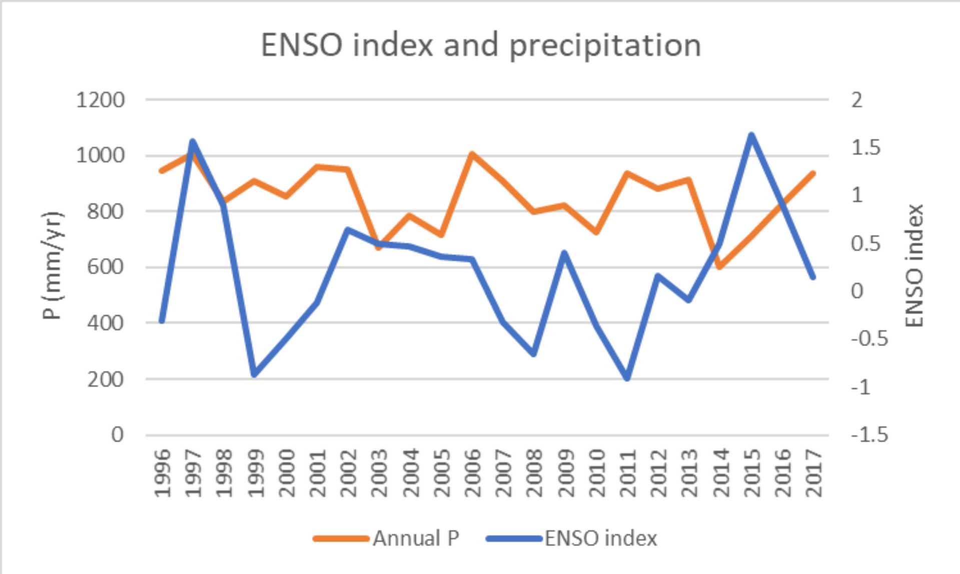


Figure 13: Number of heat waves per year.

Correlating annual precipitation and air temperature to El Niño activity is difficult (Figure 14). Therefore it is also hard to tell what the effect for eThekwini's climate would be if El Niño frequency or intensity changes in the future.



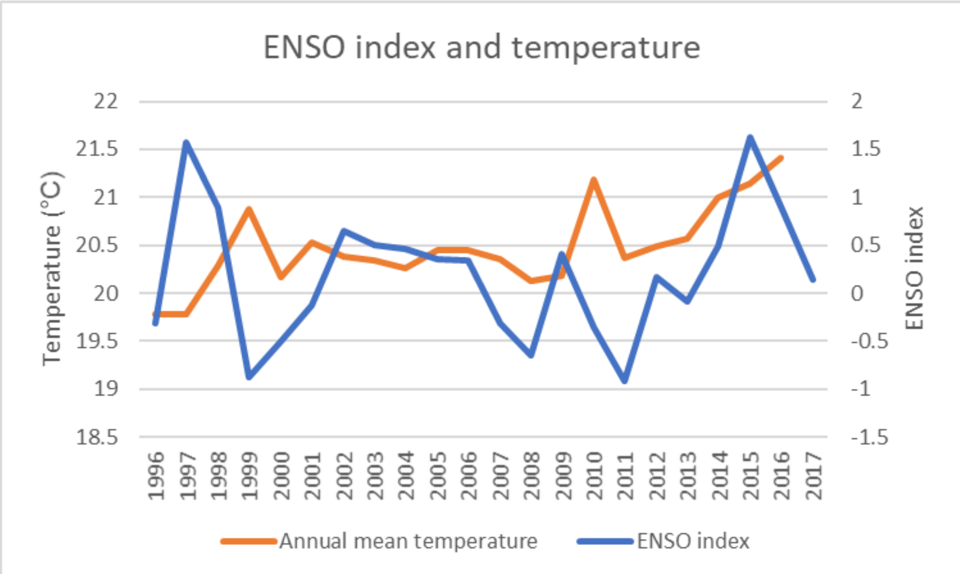


Figure 14: Correlation of El Niño Southern Oscillation index and precipitation (top) and temperature (bottom).

4 Projected changes in climate

4.1 Temperature, humidity and evaporation

Unsurprisingly, air temperature is likely to increase in the future, for mean, maximum and minimum air temperatures (Figure 15). The difference between the RCP’s is quite large, between the 1.5 °C scenario (RCP2.6) and RCP8.5 the difference is 1-2 degrees. Even meeting the 1.5 °C global target, would imply temperature increases of ~1 °C by 2050, compared to the last two decades. Extrapolating the temperature trends during the historical reference period (~1.8°C per 20 years), would reasonably well correspond to the RCP8.5 scenario. The average number of heat waves per year would stay more or less the same as during the historical reference if the 1.5 °C scenario (RCP2.6) can be realized. However, if the RCP8.5 scenarios is realized, eThekwini Municipality would face a three-fold increase in the average number of heat waves per year by 2050 (Figure 15). Extrapolating the trend in heat wave occurrence during the historical reference period would imply a doubling of the average number of heat waves per year, in between the RCP4.5 and RCP8.5 scenarios.

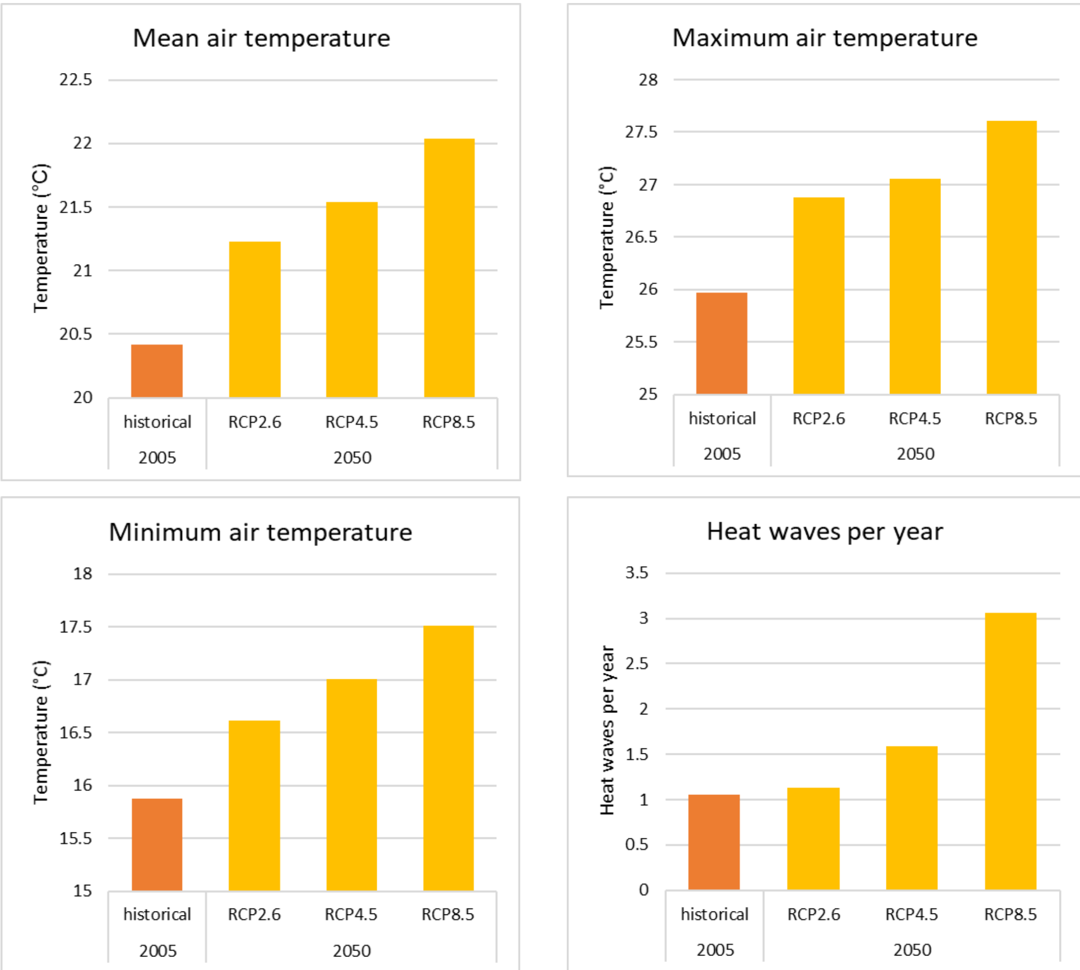


Figure 15: Projected changes in mean air temperature, maximum air temperature, minimum air temperature, and the number of heat waves per year under the different RCPs. The figure shows multi-year means. Historical (2005) is the mean of 1996-2015, the future (2050) is the mean of 2041-2060.

Figure 16: Projected seasonal changes in mean, maximum and minimum air temperature under the different RCPs. The figure shows multi-year means. Historical (2005) is the mean of 1996-2015, the future (2050) is the mean of 2041-2060.

Projected temperature increases vary per season (Figure 16). Changes in maximum air temperature in autumn and winter show lower increases for RCP4.5 compared to RCP2.6. The selected climate models do not contain projections of changes in humidity. However, analysis of future changes in relative humidity for the location of eThekwini Municipality in the entire CMIP5 climate model ensemble, shows a very slight increase in the future (from 76% for the historical period to ~78% on average). This can aggravate the perception of people experiencing the projected increases in air temperature (Giannopoulou et al. 2014). The CMIP5 ensemble shows also increasing trends in evaporation rates, for the location of eThekwini Municipality. Evaporation increases by 3% for the 1.5 degrees scenario and 6% for the RCP8.5 scenarios.

4.2 Precipitation

Future projections for precipitation are usually much more uncertain than projections for temperature. The eThekwini Municipality is no exception in this. In the future, precipitation could either increase or decrease, with most drastic changes for the strongest warming scenario (RCP8.5) (Figure 17). In particular for precipitation extremes, the changes can be large. Currently once in ten years recurring events may recur more often (once in three years), and the intensity of the most extreme events could increase. Dry years could also become more frequent. The current 10% most dry years could become the 30% most dry years in the future (Figure 19). It has to be noted that the projections for precipitation show a large spread, and therefore it is difficult to state with certainty what will happen in the future.

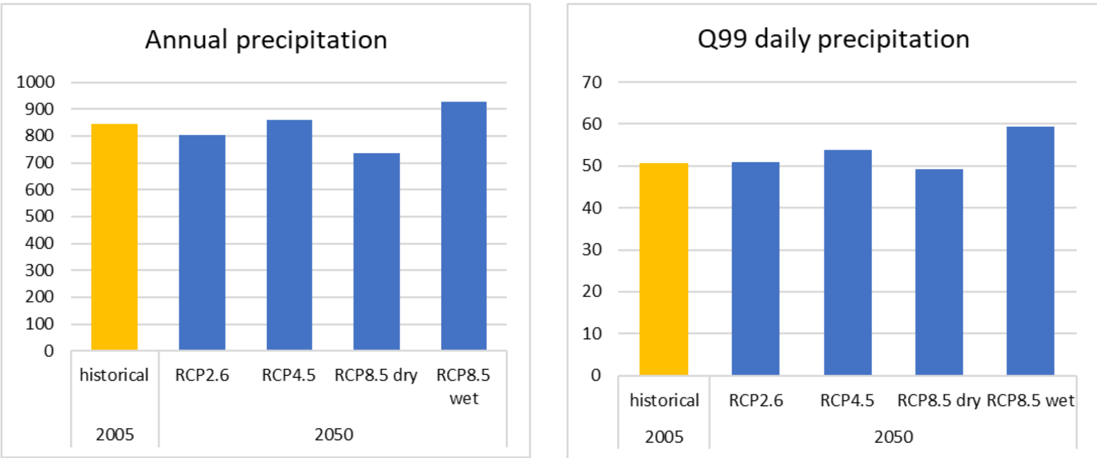


Figure 17: Changes in annual precipitation sums and Q99 (99th percentile of daily precipitation) precipitation sums. The 99th percentile of daily precipitation sums indicates the amount of precipitation falling during the top 1% of days with rain. Durban has on average 89 rain days per year, meaning that the Q99 rainfall occurs on average once in ~13.5 months). The figure shows multi-year means. Historical (2005) is the mean of 1996-2015, the future (2050) is the mean of 2041-2060.

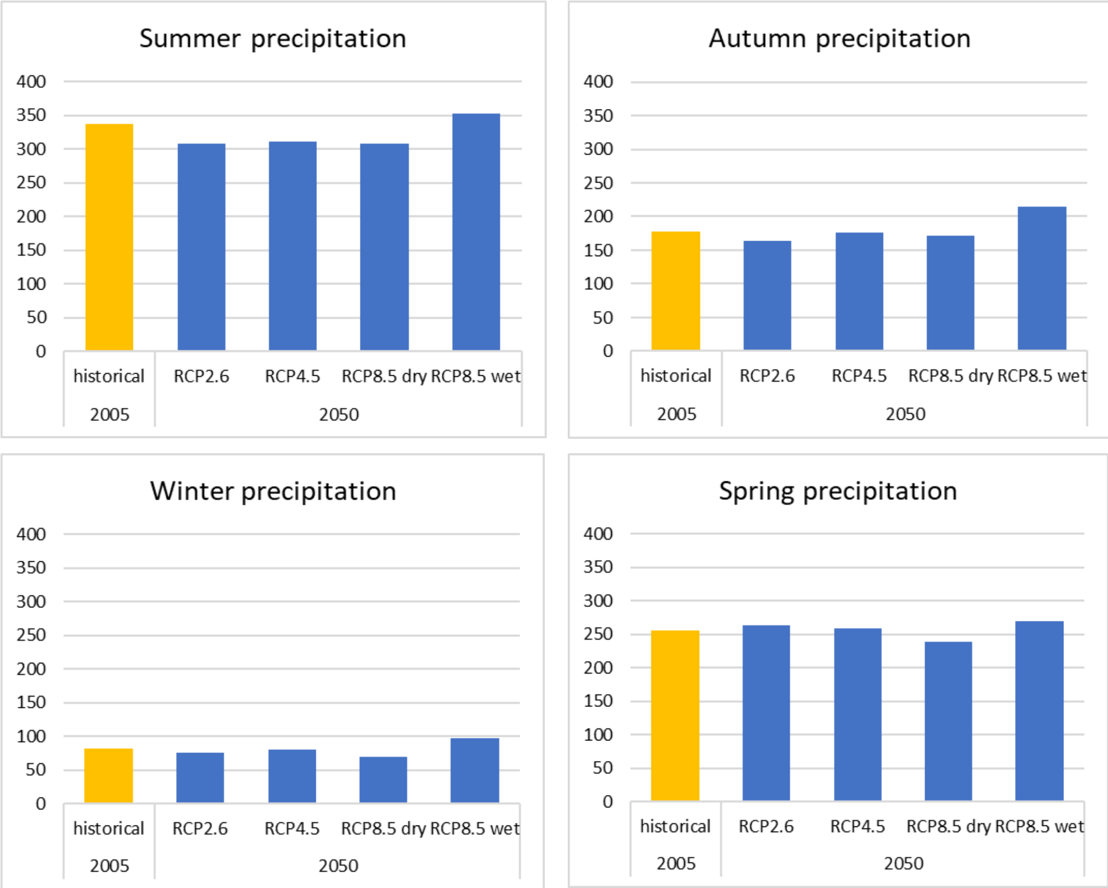


Figure 18: Changes in seasonal precipitation sums. The figure shows multi-year means. Historical (2005) is the mean of 1996-2015, the future (2050) is the mean of 2041-2060.

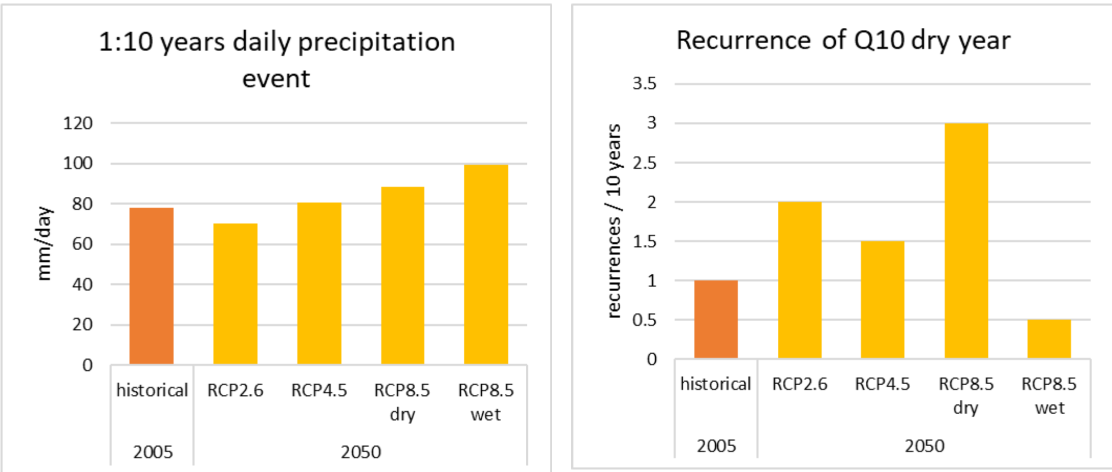


Figure 19: Changes in 1:10 years precipitation event intensity and recurrence interval of Q10 (10th percentile of annual precipitation sums). The 1:10 years precipitation event shows the daily rainfall sum for a precipitation event that occurs on average once in ten years. The Q10 dry year represents the 10% driest year during the historical period. For the future, the plot indicates how often a year with that precipitation amount occurs. The figure shows multi-year means. Historical (2005) is the mean of 1996-2015, the future (2050) is the mean of 2041-2060.

4.3 Wind speed, storm surge and sea level rise

The projections for wind speed in the selected GCMs do not show clear trends for changes in wind speed, which may be related to their resolutions. For more accurate projections, further downscaling may be required. No information on changes in wind speed for the area around eThekwini municipality is found in scientific literature. Research into storm surge and sea level rise has been conducted for the Durban area (Mather and Stretch 2012). This analysis is based on potential maximum wave heights in the future. Measurements show a linear increase in sea level for Durban, increasing by 2.7 mm/year (Mather 2007; Mather et al. 2009) (Figure 20).

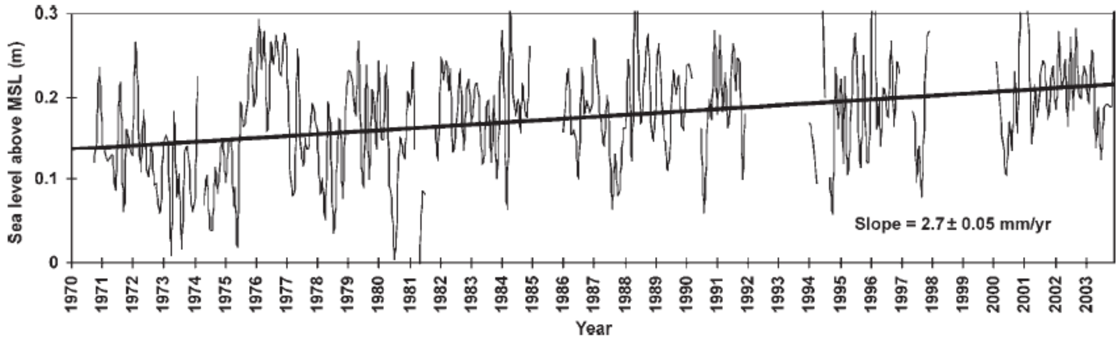


Figure 20: Increase in sea level rise in Durban (Mather 2007)**.**

The same author published regional sea level rise projections based on local temperature increase for Durban (Mather 2009) (Table 2). Using the modified Rahmstorf relationship for each degree of air temperature increase a 117 mm rise in sea level is estimated for Durban. Linking this to the updated climate change projections for eThekwini Municipality, the RCP2.6 scenario would correspond to ~117 mm additional sea level rise, the RCP4.5 scenario to 234 mm additional sea level rise and the RCP8.5 scenario to ~375 mm additional sea level rise by the end of the 21st century.

Table 2: Regional sea level rise projections based on local temperature increase for Durban. (Mather 2009)**.**

Average temperature increase (°C)	Sea level rise increase (mm)
1	117
2	234
3	351
4	468
5	585

At the global scale, the IPCC indicates global projection with sea level increases up to 1 meter (Figure 21).

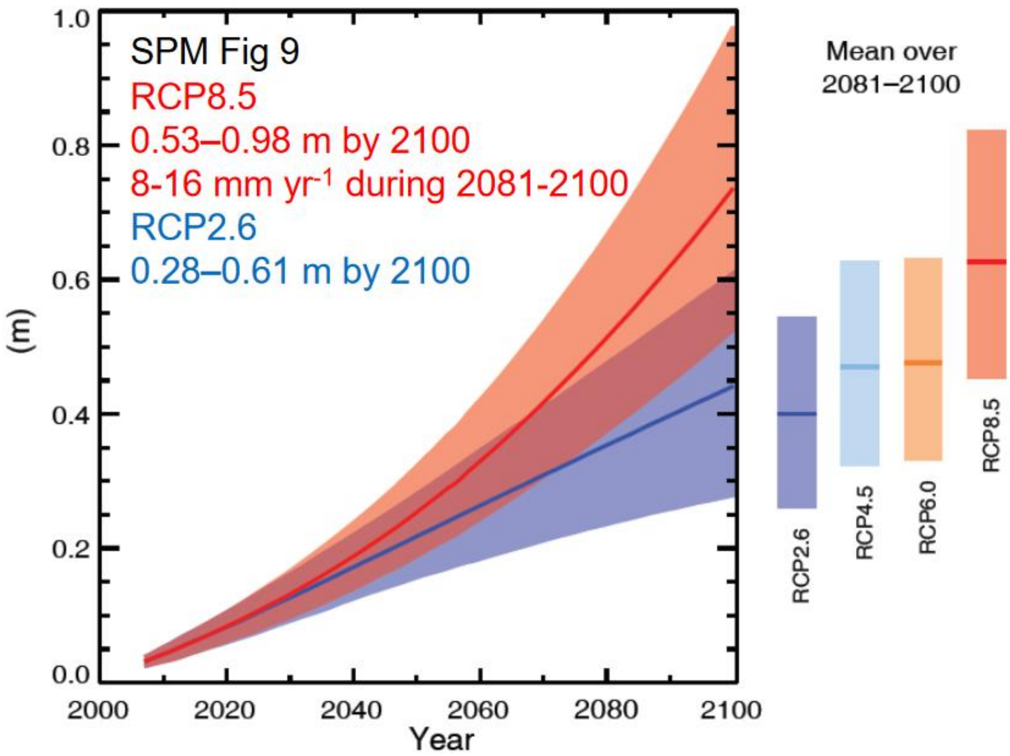


Figure 21: IPCC projected global mean sea level rise.

Globally the future changes in sea level are uncertain. For 2100 many countries take into account maximum sea level rise between 1 and 1.5 meters. An outlook into what may happen after 2100 is provided by Climate Central (http://sealevel.climatecentral.org/). Local sea level rise in Durban could be up to 8.8 m in the very long run (hundreds to thousands of years from now).

	1.5 °C	*3 °C (~RCP4.5)*	*4 °C (~RCP8.5)*
Local sea level rise (m)	2.8	6.3	8.8
2010 population below sea level from warming amount (cap)	69000	335000	537000
2010 population below sea level from warming amount (% of total)	2	11	17

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