# Climate modeling in Africa with a focus on Kenya: identifying the optimal scenario

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**Abstract:** Climate modeling in Africa plays an essential role when it comes to assessing future climate scenarios as well as their potential impacts especially in view of limited data for empirical analysis. Such modeling provides insights for engineers, and policymakers, thereby, aiding in informed decision-making for water resources utilization, agricultural production, as well as disaster preparedness. Furthermore, they support long-term climate adaptation strategies by assessing the impact of climate change on ecosystems, infrastructure, and water resources, facilitating evidence-based policy formulation for sustainable development and resilience building in Africa. There exist different climate models in the world, for example, CORDEX, GCM- CCSM4, HadGEM2-Es, RegCM4, WRF, CCLM, and CESM just to mention a few. The paper focused on climate models employed in Africa more so Kenya. Some of the identified models include, Climate Atlas Climate Model, Rossby Centre Regional Climate Model, CMIP5 Climate Model, CORDEX, and WRF. The CORDEX climate model is a regional climate model (RCM), and could be directly compared to CMIP6. Similarly, climate atlas model comprises of expert tools that are used in the evaluation of crop varieties, and a tailored solution provided. On the other hand, WRF uses a software architecture tool as well as a data assimilation system, which is then used in forecasting climate conditions. In summary, all these models help in temperature projections, precipitation patterns, sea-level rise estimates, and more, providing invaluable information for climate research, policy-making, and adaptation strategies in the complex Kenyan region.

**Keywords:** climate models, optimal scenario, futuristic weather patterns

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## 1 Introduction

This paper employs a systematic review approach to delve into the intricacies of climate modelling within the African continent. It explores the strategies employed within the climatic system to foster a more profound interaction between matter and energy. While the primary focus is on the Kenyan context, this study also sheds light on climate models utilized both on an international and regional scale. These models leverage advanced meteorological data and complex algorithms to simulate and predict local weather patterns, precipitation trends, and temperature fluctuations.

## 2 Global climate models

Climate models, as suggested by Gent (2018), enable scientists to understand the future climate system based on the past climatic conditions. It facilitates an ease in the prediction of the future based on the changes that have taken place and prevailing conditions. For instance, simulations are run and data

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collected, which is then analyzed to predict and compare with actual climate changes. Globally, climate models have been used to identify futuristic natural events like the El Nino, and are reliable systems even though they may contain errors. Their use in agriculture is gaining momentum as its one way that will help in climate change adaptability. Still, constant improvements to the climate models are made to increase their validity and reliability. Climatic models are based on a time-step concept, with each developed simulation being either too detailed or simplified (Reichle, 2023). Scientists use a hind-casting process to test and verify climate models, which is then constantly adjusted to check its accuracy in making predictions.

General circulation models (GCMs) typically operate at a broad horizontal scale, typically around 200-300 kilometres. However, when it comes to examining climate change impacts at a regional level, a process called downscaling becomes crucial. Dynamic downscaling is accomplished through the use of regional climate models (RCMs), which utilize GCMs as boundary conditions to simulate atmospheric conditions within smaller regions at a finer grid resolution, typically ranging from 10 to 50 kilometres. These RCMs excel at capturing local topography and land use variations, a level of detail that GCMs cannot match. This finer-grained approach is essential for producing accurate climate change projections tailored to specific regions.

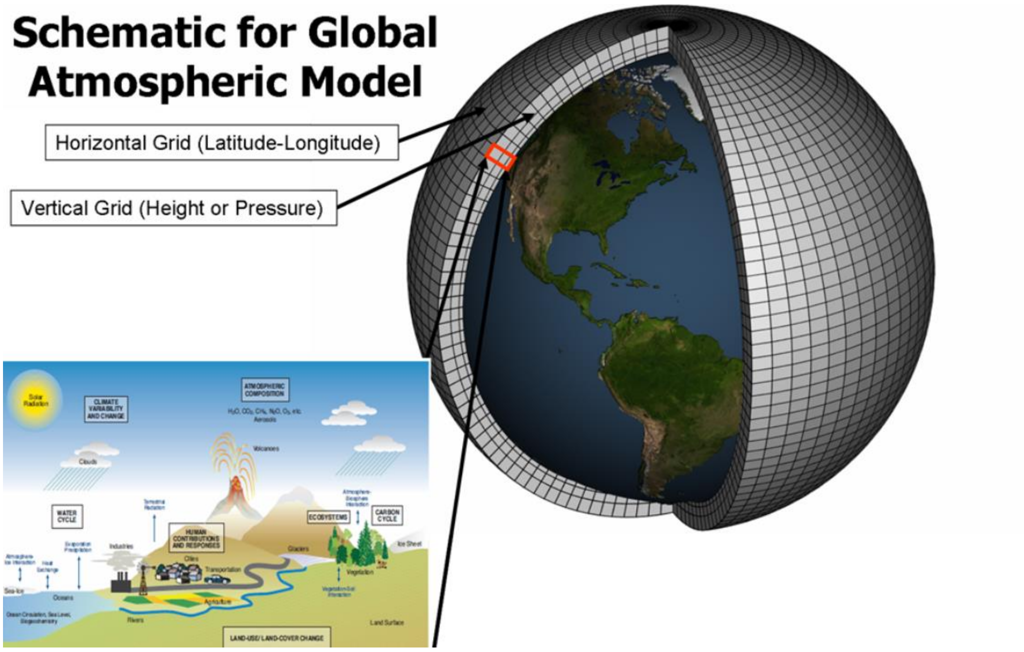


Figure 1 The climate model concept (Reichle, 2023)

The earth models of intermediate complexity (EMICs) climate model, as described by Reichle (2023), captures the geographical representation of earth in three-dimensional vector. The model is detailed, and complex based on the fact that it presents oceans, cryosphere, land, atmosphere and glaciers (Reichle, 2023). However, Thokchom (2020) argued that EMICs can be adjusted to reflect various components of the climate system based on the different components captured in a model. For instance, some models can be used to only represent ocean basins and continents only, but as Hendry et al. (2021) noted, the description detail is largely based on the technicality of the climate model. One-dimensional models are less sophisticated than the three-dimensional ones as they differentiate the geographical zones, including the oceans and atmosphere. However, some detailed EMICs may have a coarse numerical grid that eliminates the possibility of scientists understanding the impact of interactions between nature and human beings (Reichle, 2023).

The University of Victoria earth system climate model (UVIc ESCM), a modern climate model as developed by the University of Victoria, has gained global recognition due to its simplistic assessment of changes in climate (Mengis et al., 2020). A biogeochemistry ocean model, characterized with a soil model which captures the soil carbon processes as well as a permafrost carbon are captured in this model, allowing scientists to study and observe changes in historical temperature and carbon fluxes. The model has a detailed ocean model that allows scientists to evaluate constantly changing oceanic physical properties. Other additional features in the model that has allowed it to become internationally recognized is its observed tracer profile which comprise of salinity, temperature components, nitrate and phosphate spatial distribution characteristics. Kvale et al. (2021) stated that as a climate model, the UVIc ESCM produces a carbon cycle model that allows scientists to comprehend the irreversible carbon dioxide induced changes. Consistent modifications are being integrated in the UVIc ESCM model to offer a more realistic and complex representation of heat fluxes and carbon. The model has a two-dimensional atmospheric energy moisture balance as well as a wind field to offer a more-realistic visualization of the model (Pahlow et al., 2020). It's important to highlight that the UVIc ESCM model features a horizontal resolution, while its oceanic component is primarily defined by vertical layers. The thickness of these vertical layers varies, starting at approximately 50 meters near the surface and increasing to about 500 meters as you move deeper into the ocean.

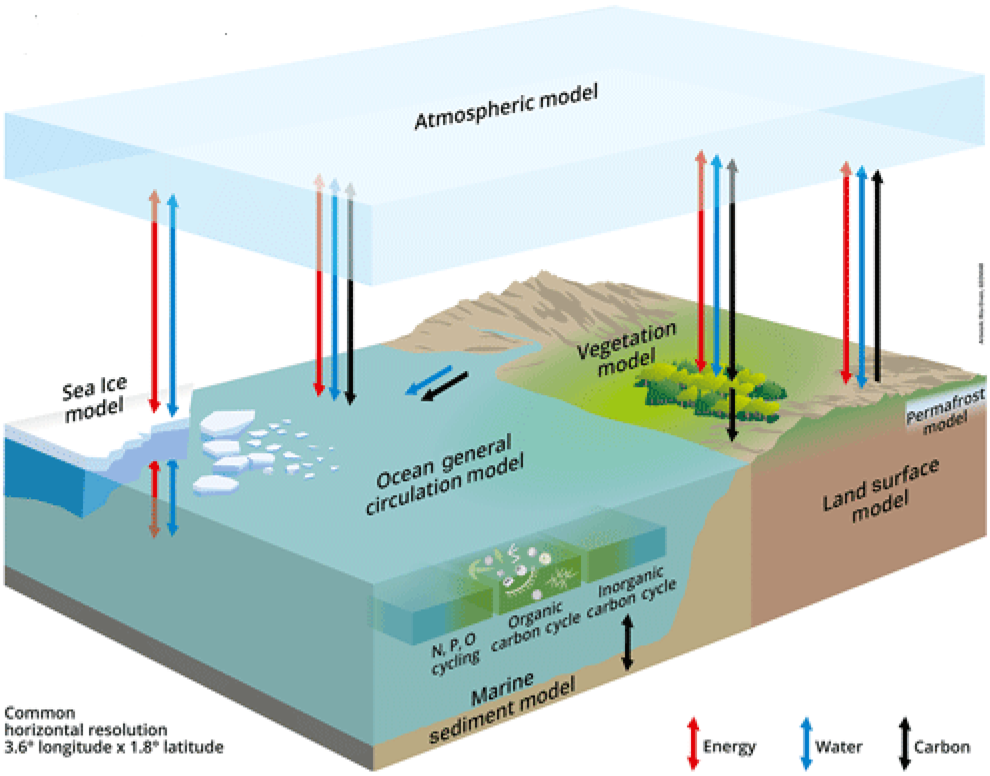


Figure 2 The UVIc ESCM climate model (Mengis et al., 2020)

The energy balance model (EBM) is based on the thermodynamics and energetics components of a climate system, allowing scientists to estimate the changes in the climate system in the world based on the energy budget (Cael et al., 2023). Since the EBMs provide a simplistic and undetailed average energy values, they are perceived to have a zero-dimension. EBMs have a possibility of being extended to two horizontal dimension and one latitude, thus capturing the heat input and output. One of the comparative advantages associated with EBMs is their ability to represent the Earth-atmosphere systems by culminating different timescales in hours, days or years (Global Climate Change, 2019; Soldatenko and Colman, 2019). These manipulations also ease the understanding of energy cycles, energy transfer processes in a transient process or steady state. Arguably, EBMs make the assumption that the radiative energy lost by the atmospheric system on Earth is equal to the solar constant (Climate Policy Watcher, 2023). The simplistic models have a capability to determine the constant temperature changes, but are limited in that they cannot explain the climatic shifts caused by the atmospheric temperature. On the other hand, complex models like (community earth system model (CESM), parallel ocean program (POP), geophysical fluid dynamics laboratory climate model (GFDL CM) etc.) have the ability to capture the energy-transfer processes on the upper layer of the ocean.

The models' spatial distribution dynamics are based on the assumption that Earth's atmospheric system is a single and uniform point, which is reflected in the division of the atmosphere into well-defined zones (Colman and Soldatenko, 2020). For instance, the one-dimension model divides the atmospheric system into latitude zones while the two-dimension model divides it into longitudinal and latitudinal directions.

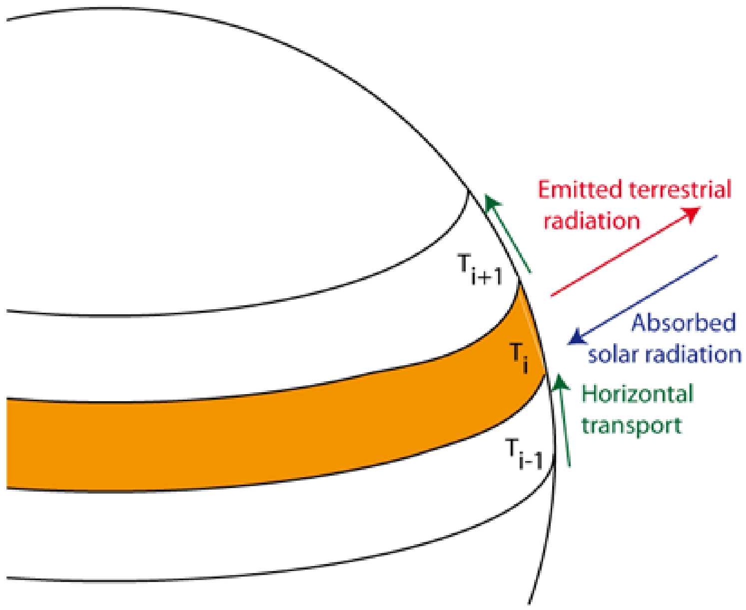


Figure 3 The one-dimensional EBM model (Global Climate Change, 2019)

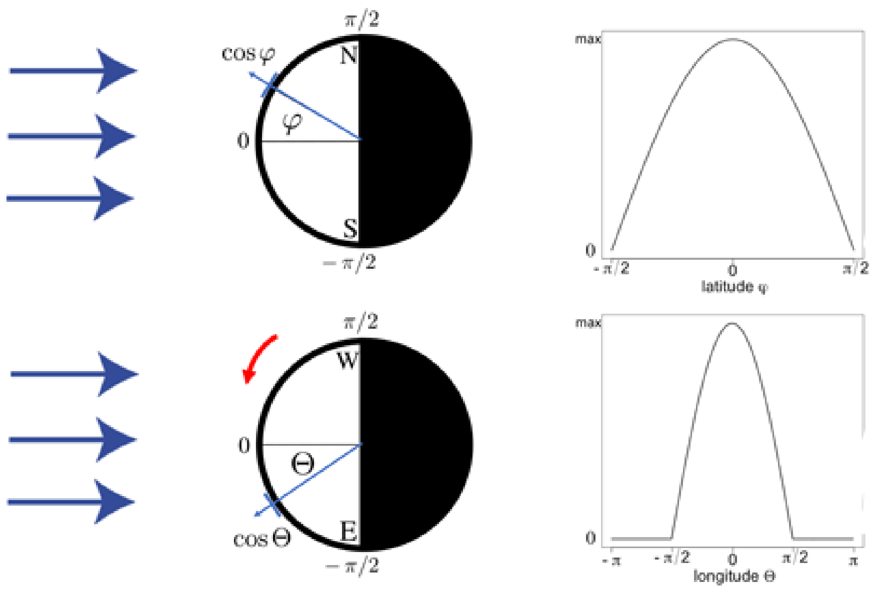


Figure 4 A spatial distribution of the energy balance of the EBM (Lohmann, 2020)

The GCMs as described by Scher and Messori (2019), is a climatic model that captures the planetary oceans and atmosphere. The models use a large-scale representation but emphasizes on transient features that are detailed, yet simplify the governing physics and empirical calculations in atmospheric dynamics. Scher (2018) argued that GCMs use a 100-500 km spatial resolution, and the vertical layers as shown in Figure 5, represent oceans and the atmosphere. A model's accuracy is increased based on its performance of the various representative aspects including humidity surface radiation and time step intervals (Penn State University, 2023). Global spectral models (GSMs) provide a physical and geographical estimate of a region's climate change, and they have the ability to demonstrate the increasing greenhouse gas emissions and concentrations in the world (Fajardo et al., 2020; Ribeiro et al., 2021). The GSMs structure as suggested by Fajardo et al. (2020), is in three-dimension, representing the interplay of the ocean, air and land domains, with each cell in the model allowing a better approximate of Earth. Technological advancement has contributed to the simplified climate model which enables scientists to demonstrate climatic changes on a regional scale, and can also be used to reflect changes in countries and states.

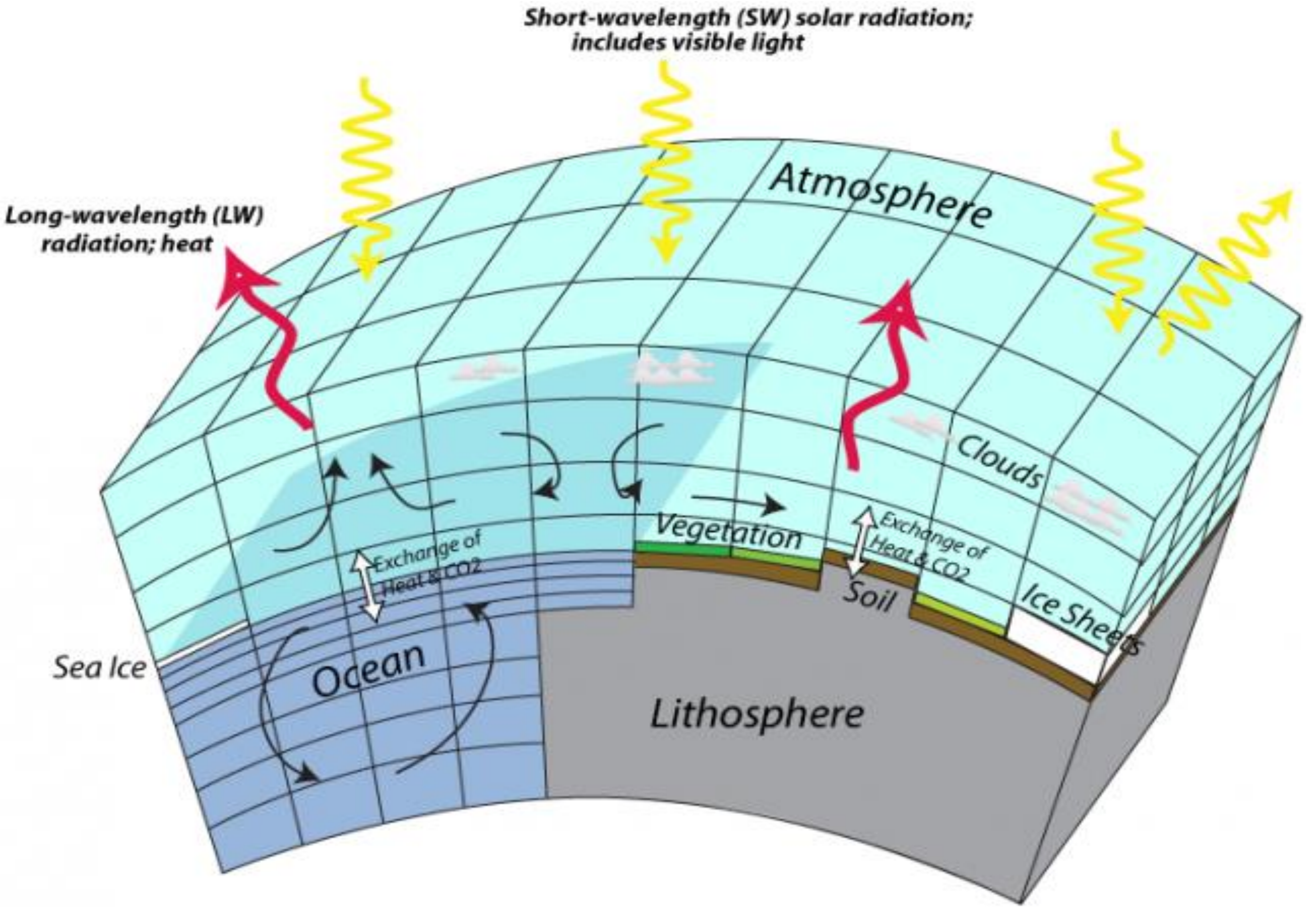


Figure 5 The GCM climate model (Penn State University, 2023)

Climate models with high horizontal resolution have smaller grid cells and can capture fine-scale features like local weather patterns, mountains, and coastlines. It has a nominal resolution of approximately 0.25 degrees. The medium-resolution configuration had a nominal resolution of approximately 1.4 degrees. Models with low horizontal resolution, on the other hand, have larger grid cells and are more suitable for simulating large-scale climate phenomena. It has a configuration of approximately 3.75 degrees in latitude and longitude.

The table below summarizes the various climate models employed globally and areas of their application.

**Table 1 Summary of various climate models**

| Climate model | Description | Area of focus | Resolution | Country of origin | Application |
|---|---|---|---|---|---|
| **GCM-CCSM4** | Community climate system model version 4 | Global | Various resolutions | USA | General climate projections |
| **HadGEM2-ES** | Hadley centre global environmental model 2- earth system | Global | Various resolutions | UK | Long-term climate predictions |
| **ACCESS-ESM1** | Australian community climate and earth system simulator-earth system model 1 | Global | Various resolutions | Australia | Climate variability and change |
| **RegCM4** | Regional climate model version 4 | Regional (Africa) | High resolution | Italy | Localized climate projections |
| **WRF** | Weather research and forecasting model | Regional (Various) | Variable resolutions | USA | Short-to medium –term weather forecasting |
| **CCLM** | Cosmo-CLM (Consortium for small scale modeling climate limited area modeling) | Regional (Europe) | High resolution | Germany | Climate impact assessment |
| **REMO** | Regional climate model | Regional (Europe) | High resolution | Germany | Climate change scenarios for Europe |
| **CCSM4** | Community climate system model version 4 | Global | Various resolutions | USA | Ocean-atmosphere interactions |
| **MIROC-ESM** | Model for interdisciplinary research on climate-earth system model | Global | Various resolutions | Japan | Carbon cycle and climate feedbacks |
| **CESM** | Community earth system model | Global | Various resolutions | USA | Multidisciplinary climate research |

## 3 Climate models in Africa

According to Laux et al. (2021), GCMs have been generally used in the African context, but due to the actual temperature and boundary conditions in the region, (RCM simulations have been formulated and used in the continent. Similarly, Bush et al. (2020) claimed that Africa’s countries differ, with some being vulnerable to severe heat stress, while others experience extreme rainfall events with possibilities of flooding and agricultural activities. This justifies why African climate is challenging for the existing models, and modifications are made to customize the diverse weather conditions in the continent. Africa is prone to climate and weather variability, which justifies the application of RCMs. Laux et al. (2021) emphasized that RCMs are relevant in providing information used by farmers in the African context, as it helps them understand the changing climatic conditions and how their agricultural activities are also affected.

### 3.1 The Met Office unified model (UM) in Central Africa

The Met Office unified model (UM), originally developed in the UK, is recognized in the African continent due to its simple structure as it accommodates a horizontal grid spacing of between 4.5 km to 25 km (James et al., 2018). Taguela et al. (2022) conducted a study on the Central African complex climatic change, using atmospheric formulations, and it was easy to identify and predict the different seasons in the region. For instance, the Atlantic-Congo zone experienced a simulated sinking, which had been caused by increased surface temperatures and pressure gradient as stipulated in the results and findings section by Taguela et al. (2022). The UM model increased the knowledge surrounding the climate conditions in the region, and it was easy to predict the future based on the collected data. The UM is managed and operated through interconnected supercomputers, and one of the comparative advantages of this model is that it has a structured ocean model that runs on request or on command. James et al. (2018) noted that the model presents different vertical and horizontal resolutions which can be compared and analyzed and a detailed report provided based on the available data sets.

The UM model is also capable of increasing resolutions in lower-resolution systems as that of the African continent, which allows periodical forecasting. This is despite the model requiring a high level of governance and control to increase the reliability and validity of produced results (Bush et al., 2020). The Met Office Unified Model is most preferred in the African context due to its seamless characteristic as suggested by Crown (2023), in that it can be used in different spatial and temporal scales, and produce high quality information. For instance, this climatic model produces a strong convection of the Indian Ocean base, including the seasonal cycles and circulation patterns.

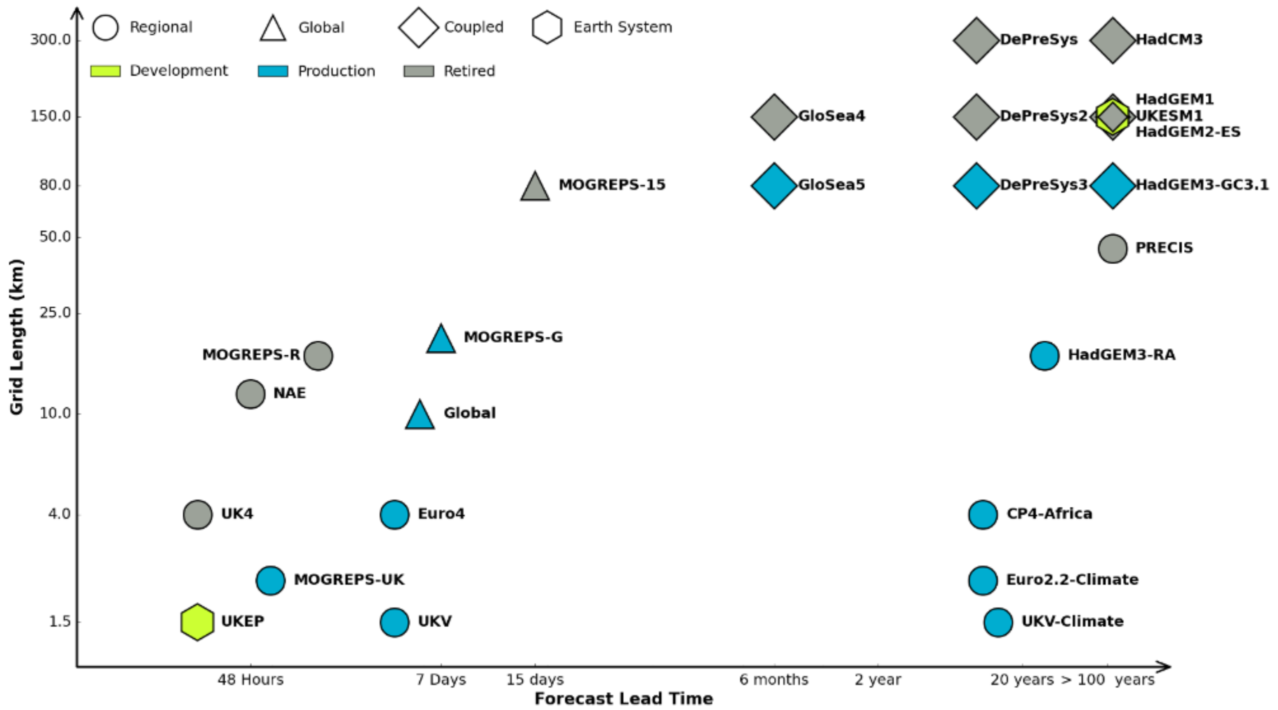


Figure 6 Illustration of the Unified Model seamless modelling hierarchy based on Met Office configurations (Crown, 2023)

The UM model as described by James et al. (2018), has an ability of broadening the hierarchy capabilities, and simplifying the data collected in planetary atmosphere. Simulations on the model reflect the cool and humid conditions on the boundary layer and on the sea surface. This is critical as it informs and influences the variation of crops planted in each region based on the specific climatic conditions. The complex and unpredictable African climate conditions become easy to understand and configure. Maher and Earnshaw (2022) suggested that the different parameterizations can be switched on and off, and is dependent on the use of information.

3.1.1 The statistical downscaling model (SDSM) climate model in West and East Africa

Siabi et al. (2023) stated that the statistical downscaling model (SDSM) is one of the most reliable climate models used in the African continent to evaluate and assess the unreliable climate changes in the region. Statistical models as suggested by Jaiswal et al. (2020) are preferred and used due to their ability to produce precise information and data about a location’s weather and climate changes. A statistical relationship between large-scale climate variables is compared with the local-scale variables, and a detailed report is generated. The justification for using the SDSM model in Africa is because its performance was perceived to be relatively high compared to the traditional weather generators and predictors (Keller et al., 2022). This means results from this model are more reliable and valid in making agriculture-based decisions. For instance, data collected from the SDSM model capture and provide rainfall characteristics as well as temperature changes.

Siabi et al. (2021) claimed the SDSM model has been widely used in East Africa, with a bias in Ethiopia and Tanzania, and has been used due to the vulnerable climate changes. The region can either be too dry or have unpredictable floods, but with climate data being collected and analyzed using the SDSM climate model, then the East African countries are able to make timely decisions and mitigate the negative impacts of negative climate changes.

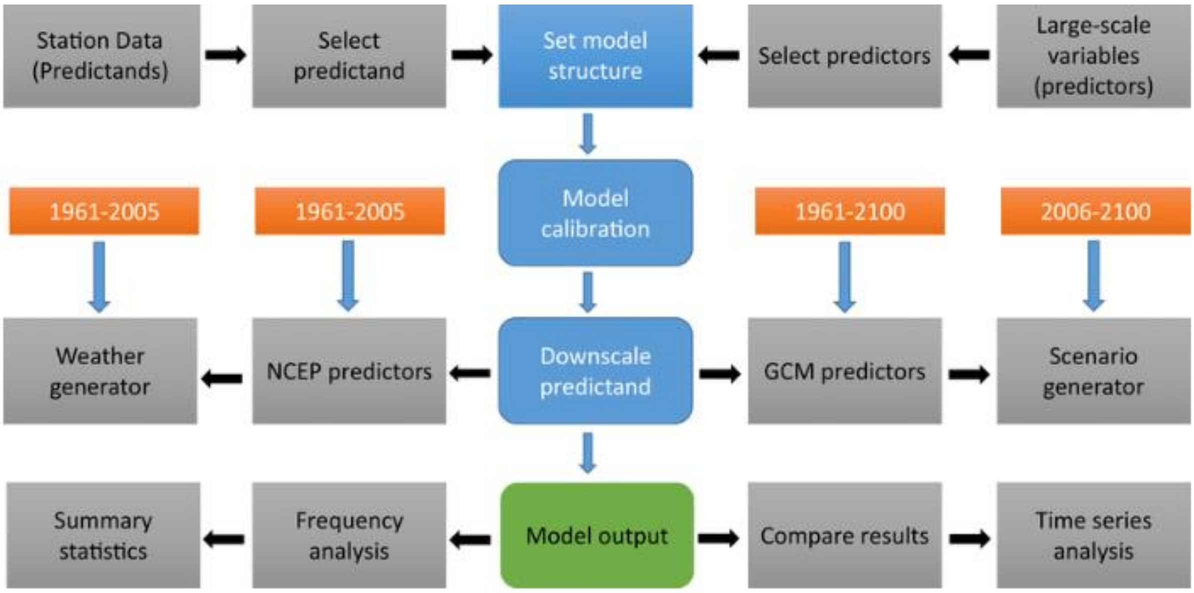


Figure 7 The SDSM climate model (Gebrechorkos et al., 2019)

The SDSM climate model has been incorporated and adopted in the East African context due to its spatial coverage dimensions, accessibility and quality of information it provides. Gebrechorkos et al. (2019) stated that the SDSM climate model's functionality can be used to reconstruct and predict relationships, and since it stores a large dataset, it becomes simplistic to retrieve historic data. The climate model is also used due to its adaptation planning abilities, which means climate changes over a period of time are used to predict what will happen in the future. Most geographical locations in Africa face the challenge of having minimal information related to data, but the SDSM model overcomes this challenge since it can be manipulated to adapt to the different locational needs (Keller et al., 2022; Siabi et al., 2023). Comparatively, the Western part of Africa is characterized with dry climatic conditions, and when adopted to study the climate changes in the region, it is able to simulate information which can then be critically analyzed to provide unbiased results (Siabi et al., 2021). The SDSM climate model downscales information by applying a statistical downscaling (SD) tool. For instance, a regression model or a stochastic bias-correction technique can be used to increase the validity of results generated after the application of the SDSM tool.

### 3.1.2 The HadGEM3-GC2 climate model

The Hadley Centre global environmental model version 3 at the global coupled model 2.0 configurations (HadGEM3-GC2) climate model is configured to the atmospheric changes as suggested by Dosio et al. (2019). This climate model, as suggested by James et al. (2018), uses a high-resolution approach to evaluate the changes in the atmosphere, land surface, ocean and sea ice components. Moat et al. (2019) argued that the HadGEM3-GC2 climate model is an improved version of the UM climate model since they have similar dynamics and features, with the only difference being that the latter is more sophisticated and complicated. The HadGEM3-GC2 climate model, within the African context, provides a useful and detailed basis through which the analysis is done. The

HadGEM3-GC2 climate model collects information related to the long-wave and short-wave components, noting the significant changes that take place. At the global level, any change in the atmospheric resolution is an indicator or signal that there is a climate change (James et al., 2018). This is noted in the tropical rainfall changes or intense storms, or in some instances, sea ice. The climate model conserves energy and its configurations allows it to have a three-hour time average reading as opposed to a twenty-four-hour period. Dosio et al. (2019) noted that the coupling fields have a new frequency which is consistent with the momentum fluxes. Additionally, the vertical and lateral ocean heat transports in the HadGEM3-GC2 climate model are associated with the Indian Ocean resolutions and model, justifying its adoption in the African continent as it aligns with the shallow and deep ocean beds in Africa.

The reduced precipitation levels in West Africa do not limit the HadGEM3-GC2 climate model from collecting atmospheric simulations since the model consist of a dry bias that enables it to constantly adjust to the unstable weather patterns in the region. Moat et al. (2019) stated that the HadGEM3-GC2 climate model is characterized with an accurate simulation of clouds, which enables professionals collecting and analyzing climate related information to evaluate and understand cloud properties like its height and amount. The West African side of the continent has tropical heat and low altitude, which can either be a thicker or thin cirrus, but such limitations are eliminated through the improved simulation capabilities in the HadGEM3-GC2 climate model (Dosio et al., 2019).

3.1.3 The climate model intercomparison project (CMIP)

They are a collection of global climate models developed by research institutions worldwide. The climate model intercomparison project (CMIP) climate model, as suggested by Ayugi et al. (2021b), studies and examines the coupled atmosphere-ocean general circulation output. The CMIP5, also known as project phase 5, was an experimental climate model that supported atmospheric only simulations, long-term simulations as well as hindcasts simulations. These components would then be used to evaluate and predict future climate changes using both a short-term and a long-term time scale. The CMIP climate model has been adopted within the African context due to its ability to increase understanding of climate changes based on the past and present, which are as a result of radiative forces, natural or unforced variability (Choi et al., 2022; Samuel et al., 2023). Idealized experiments are conducted regularly which support the predictability of the climate system, taking into consideration that space and time scales are never constant. Data collected is analyzed and presented in a standardized format that is easy to interpret, and this is used to make decisions. Mwanthi et al. (2023) stated that the CMIP6 climate model, which is an improved version of the CMIP5 version, has been adopted in the East, West and Central parts of Africa to determine the coupling processes between the atmosphere and land and to evaluate soil moisture content. The climate model is designed to collect atmospheric data in both a stable and unstable surface, which is reflected in the soil moisture anomalies. According to the World Climate Research Programme (2022), the current CMIP climate model is at stage 8.

The CMIP5 and CMIP6 climate models have always been characterized with idealized experiments that not only examine cloud-climate feedbacks, but climate change impacts on the availability and demand of water used for irrigation purposes as suggested by Dutta and Maity (2022) and Nkiaka et al. (2018). This is relevant within the African continent due to the arid and semi-arid climatic conditions that necessitate the use of irrigation based agricultural activities to support agriculture and subsequent food production. The CMIP5 climate model is also used to conduct a process-oriented diagnostics, including, but not limited to physical tendencies and high-frequency outputs as described by Mwanthi et al. (2023). The frequency outputs are customized to collect data regularly and within short-time periods.

Comparatively, Ayugi et al. (2021b) and Li et al. (2019) stated that the CMIP6 model has more accurate climate projections as constant improvements and adjustments are introduced to curb the weaknesses and limitations that existed in the previous models. For instance, the CMIP6 climate model has an assorted range of socioeconomic pathways, which are relevant in the African context understanding of climate changes due to food production and security, and large volumes of dataset can also be collected within a short-period. CMIP models offer a range of resolutions and complexities, making them valuable for assessing large-scale climate changes in Africa.

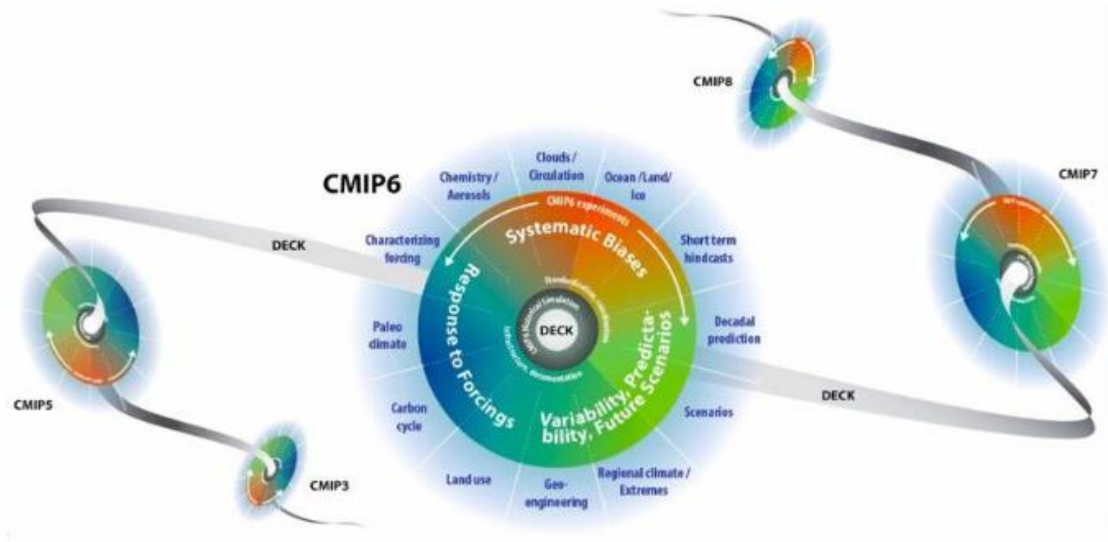


Figure 8 Development and changes in the CMIP climate models (World Climate Research Programme, 2022)

### 3.2 Climate models in Kenya

Kenya, a developing economy, has been at the forefront in formulating policies and strategies to enhance its understanding of climate changes in the region, which are meant to improve the agricultural production decisions as suggested by Matsaba et al. (2021). Potential risks and mitigation strategies related to climate changes are relevant to Kenya, justifying the development and design of climate models customized for the Kenyan climate dynamics. The unreliable and unpredictable climate in Kenya become easy to manipulate and manage once enough data has been collected about the different geographical areas.

3.2.1 The Climate Atlas climate model

According to Patrick et al. (2020), Kenya's Jomo Kenyatta University of Agriculture and Technology developed and designed the first customized climate model system, whose functionalities and features could be traced back to the Netherlands. With the climate model also being designed and operated in Indonesia and Bangladesh, also growing economies, Kenya's developers are confident that the climate model will help resolve the underlying food insecurity issues in the region. The climate model, which is at its initial stages, is structured to provide relevant stakeholders in the economy with futuristic weather patterns and scenarios, which can then be used to make current decisions (Kogo et al., 2021: Matsaba et al., 2021). The justification for the development of the Climate Atlas model is that despite the world having diverse climate modelling systems, none had been personalized to fit the specific needs of the country. Additionally, the climate model allows users to collect and analyze information from different locations within the country, taking into consideration that some regions have high temperatures and rainfall, while others are characterized with low temperatures and rainfall in each year (Nunow et al., 2020). By understanding the changes that happen within each specific location, Kenya's policymakers would localize decisions based on each location as opposed to generalizing the entire region.

The Climate Atlas climate model when in operation will enable Kenya to shift its approaches and policies to align with the internationally recognized resilient crop varieties which will be pertinent in improving and rectifying problems associated with floods and droughts (Nunow et al., 2020). Food security in Kenya is an underlying problem that affects a large percentage of its population, but with the climate model being used to study and understand the climate conditions of every geographic location in the country, it will be easy to invest in a long-term and permanent climate mapping strategies. For instance, irrigation could be used in semi-arid and arid areas, and greenhouses could be alternative measures to increase production in regions that have regular rainfall. Kajiado and Kiambu counties in Kenya have adopted the user-oriented climate model, whose interactive feature allows farmers and other users to make climate decisions and plan the future based on the changing climatic conditions in the areas (Matsaba et al., 2021). The climate model comprises of expert tools that are used in the evaluation of crop varieties, and a tailored solution provided.

3.2.2 Rossby centre regional climate model

Ayugi et al. (2020) stated that the Rossby centre regional climate model, within the Kenyan context, could be perceived as a regional based climate model, which facilitates forecasting climate conditions in the country. Notably, Ongoma et al. (2018) claimed that the region climate model may be characterized with high margins of errors due to the limited information on spatial resolutions, but this limitation could be eliminated through the application of more than a single RCM. The quantile mapping bias correction (QMBC) is a preferred strategy to rectify the underlying problems as described by Ayugi et al. (2018), justifying the adoption and use of the Rossby centre climate model in Kenya.

Mugo et al. (2020) stated that with the existing challenges associated with RCMs, bias-correcting models are necessary to help eliminate subjective opinions, and instead, increase the validity and reliability of results and findings. For instance, Kenya experiences long and short rains, respectively, in the periods between March and May, and October and December, and this allows professionals and stakeholders involved in studying and interpreting the weather to collect data during those specific months. The decrease or increase in rainfall levels could then be explained using other existing phenomenon like global warming, but this would be dependent on the rainfall spatial extent (Ayugi et al., 2018; Mugo et al., 2020). Additionally, in the event that rainfall patterns, when comparing the past and present, are noted, then policymakers have a responsibility of sensitizing and creating awareness amongst farmers on adjusting their planting seasons.

3.2.3 The CMIP5 climate model

Tan et al. (2020) argued that the CMIP5 climate model framework is internationally recognized, but through the RCM approach, could be localized to the Kenyan context, increasing the understanding and dynamics of the climatic conditions in the region. Mumo and Yu (2020) stated that a simulation of the CMIP5 climate model to initiate consistent patterns was used to study the rainfall datasets in Kenya, and to understand how the Indian ocean influences the short and long-rain periods in the region. With the global circulation models (GCMs) acting as background knowledge through which rainfall could be studied, the adoption of the CMIP5 model was simplistic, and it was easy to not only collect, but analyze information related to the climate aspects in Kenya. Ayugi et al. (2021a) argued that with the CMIP climate models undergoing constant changes and modifications, their ability to simulate climate patterns becomes simplified, and the algorithms can be explained correctly. Teleconnection links are not permanent, as they change based on climatic conditions, and this could be perceived as one of the driving factors towards rainfall changes in Kenya (Mumo and Yu, 2020). The CMIP5 model made it easy for the researchers to not only identify but explain how variations in the sea temperature in the Indian ocean have directly influenced the changes in rainfall seasons in the country.

Kenya's climate change vulnerability as suggested by King and Washington (2021) is evidenced by its irregular rainfall patterns which has an effect on food production abilities in the region. The absence of proper climate models in the country has resulted in uncertainty in rainfall change and management. However, this could be eliminated through the Coupled Model Intercomparison Project Phase 5 (CMIP5) climate model, which, as described by King and Washington (2021), could be used in the examination of the changes in the Indian ocean currents, and how this affects rainfall in Kenya. The country has two major rainfall seasons occurring twice per year, but despite this knowledge in climatic changes in Kenya, the region has faced severe drought and famine. The CMIP5 model systematic bias on Kenya's rainfall could be explained through the estimations made on the amount of rainfall expected in the last quarter of the year (Muhati et al., 2018). Additionally, the climate model presents detailed information related to how the rate of precipitation affects the spatial patterns in the zones.

3.2.4 The coordinated regional climate downscaling experiment (CORDEX)

The coordinated regional climate downscaling experiment (CORDEX) is an RCM, whose main objective in the Kenyan context is to simulate rainfall patterns and possibly trigger a pattern (Luhunga et al., 2018; Mukhala et al., 2017). CORDEX, initiated and supported by the World Climate Research Program, creates an enabling environment through which regional climate and rainfall projections could be made with ease. With steady and regular rainfall, it was possible to eliminate and stabilize the negative impact of low rainfall levels on crop production and food security. Conflicts associated with food scarcity also end. However, Jacob et al. (2020) stated that the probability of the CORDEX climate model to be used and viable in the Kenyan context could be evaluated to ensure that it can be successfully used to generate downscaled projections.

The CORDEX climate model as suggested by Sørland et al. (2021), is a RCM, and could be directly compared to CMIP6. The justification for this is that CORDEX assesses any form of uncertainty as it acts as a diagnostic tool. For instance, in Kenya, the Tana River County which is highly vulnerable to climate variability and changes, could be properly be evaluated through the CORDEX RCM, which is made possible through the adjustments and modifications to cater for the exact climatic conditions in the region (Ouédraogo et al., 2019). For instance, validation tests and assessments are conducted to verify the past climatic conditions in the region, and this is compared against the agricultural production capabilities. An informed decision is made after the statistical downscaling approach which reveals whether or not the short and long rains in the region are reliable, and which crops are sustainable based on the prevailing conditions.

3.2.5 The weather research and forecasting model (WRF)

Kerandi et al. (2018) described the weather research and forecasting model (WRF) as a numerical weather prediction tool whose design allows it to capture atmospheric information. As a climate model within the Kenyan context, the WRF uses a software architecture tool as well as a data assimilation system, which is then used in forecasting climate conditions. This model is flexible, making it efficient and relevant for the Kenyan weather conditions based on the observations and analyses conducted. Kenya is geographically located within the Equator, and this makes it have a dry climatic condition compared to other equatorial regions across the world (Messmer et al., 2021; Njuki et al., 2022). The precipitation patterns in Kenya are heterogeneous, which could be explained by the surrounding natural resources including the lakes, the Indian ocean, topographical design and the tropical circulation. For instance, in Kenya, the dry Turkana region has a low precipitation rate, which is responsible for the suppressed rainy seasons in the area. The unreliable rainfall makes it almost impossible for the locals residing in such areas to plant sustainable crops. However, through the WRF climate model, professionals in matters related to weather and climate are able to evaluate the content of moisture in the soil, and make better predictions about the prevailing conditions.

The WRF simplifies the observation and interpretation of weather patterns in the complex Kenyan region as suggested by Njuki et al. (2022). There is no dominant climatic condition in Kenya, and simulations done through the MRF model provide a detailed solution and approach through which predictions can be made about the weather. This is done through modifications to fit the region’s precipitation and distribution dynamics. Kerandi et al. (2018) stated that through the WRF climate model, an estimated precipitation and spatial pattern could be captured of the Lake Victoria basin region in Kenya. This is done over a 50 km horizontal resolution, but this could be reduced to around 25 km to increase the validity of the generated findings. The WRF climate model has also been applied in other regions in Kenyan, including the Mount Kenya region, whose weather patterns and topography is different from that of the Lake Victoria basin (Njuki et al., 2022). The WRF model downscales boundary and initial conditions.

## 4 Conclusion

The various arrays of climate models tend to play an essential role when it comes to understanding of diverse climatic systems. The various models covering both global and regional scales offer valuable insights into the potential impacts of climate change and helps in formulating informed strategies for adaptation as well as mitigation. With the help of advanced simulations, these models enable engineers and policymakers to explore various scenarios and identify optimal pathways for sustainable development. From the Kenyan context, five models were identified, namely; Climate Atlas climate model, Rossby Centre Regional climate model, CMIP5 climate model, CORDEX, and WRF. Climate Atlas climate model is structured to provide relevant stakeholders in the economy with futuristic weather patterns and scenarios, which can then be used to make current decisions. Similarly, Rossby Centre climate model is useful when it comes to increasing the understanding and dynamics of the climatic conditions in the region.

CORDEX models provide high spatial resolution compared to GCMs, which is important for Kenya due to its significant climatic variations over short distances caused by diverse topography and geographical features. They can capture topographical variations more effectively, considering Kenya's varied landscape, encompassing highlands, lowlands, and coastal areas. These models also incorporate regional climate drivers like the Indian Ocean Dipole (IOD) and El Niño Southern Oscillation (ENSO), impacting Kenya's climate with variations in rainfall patterns, droughts, and floods. Furthermore, CORDEX models contribute to assessing localized impacts such as water scarcity, food security, and disease outbreaks, supporting informed decisions and adaptation strategies by engineers, policymakers, and stakeholders. While crucial for research, it's imperative to rigorously validate CORDEX models against historical climate data to ensure accuracy and reliability for the Kenyan region.

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