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The current issue is the third of the eleventh volume of the *Athens Journal of Sciences (AJS),* published by Natural & Formal Sciences Division of ATINER.

Gregory T. Papanikos, President, ATINER.

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- Abstract Submission: **17 December 2024**
- Acceptance of Abstract: 4 Weeks after Submission
- Submission of Paper: **23 June 2025**

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- Greek Night Entertainment (This is the official dinner of the conference)
- Athens Sightseeing: Old and New-An Educational Urban Walk
- Social Dinner
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- Exploration of the Aegean Islands
- Delphi Visit
- Ancient Corinth and Cape Sounion

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Conference fees vary from 400€ to 2000€
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Long-term Variations in Heat Storage in the South-eastern Mediterranean Sea

By Tarek M. El-Geziry[*], Ibrahim A. Maiyza[±] & Shimaa I. Maiyza[°]

Heat storage (HS) plays an essential role in the dynamic of oceans and seas. Hence, it is important to examine the behaviour of change in the HS at the different water layers; as this may have impact on other ocean processes and biotic systems. This study attempts to investigate the long-term variations in the HS at the upper 100 and 300 m layers in the south-eastern Mediterranean region. It depends on hydrographic data (temperature and salinity) collected over the period 1948-2021. The examination of trends was carried out using the linear regression approach for the calculated HS. Results revealed a significant decreasing annual trend of -3.94E6 Jm^{-2}/yr at the 100 m-layer, and a non-significant decreasing trend of -0.0037E9 Jm^{-2}/yr at the 300 m-layer. The quadratic regression approach was used to assess any cyclicity in the HS. Results revealed cyclic behaviour of changes in HS at the two layers of interest, but with different minimum years of occurrence. While at the 100 m-layer the minimum year of occurrence was 1992, it was 1989 at the 300 m-layer. This may be attributed to both the dynamical processes taken place at each layer and to the criteria of the water masses spreading over the different depths in the south-eastern Mediterranean region. Further investigation on the relationship between HS and other biotic features in the south-eastern Mediterranean region is still needed.

Keywords: *heat storage, cycles, trends, South-eastern Mediterranean*

Introduction

Heat storage (HS) plays an essential role in the dynamic of oceans and seas. 80% of the excess heat caused by anthropogenic activities now dwells in the ocean (Levitus et al. 2005), and therefore, the ocean heat content is a fundamental indicator of the alteration in the Earth's radiative balance. Moreover, ocean heat content significantly impacts the sea level rise (SLR) via extended thermal expansion process (steric effect, Domingues et al. 2008). Owing to the seawater high heat capacity, even slight variations in seawater temperature result in a significant amount of HS and a significant rise in the ocean heat content (Kubin et al. 2023). The HS in the upper layers of oceans is subjected to considerable spatiotemporal changes due to variations in seawater temperature and salinity

[*]Professor and Head, Laboratory of Physical Oceanography, Division of Marine Environment, National Institute of Oceanography and Fisheries (NIOF), Egypt.
[±]Emeritus Professor, Laboratory of Physical Oceanography, Division of Marine Environment, National Institute of Oceanography and Fisheries (NIOF), Egypt.
[°]Associate Professor, Laboratory of Fish Economy and Statistics, Division of Fisheries, National Institute of Oceanography and Fisheries (NIOF), Egypt.

either on zonal or meridional basis as well as from one season to another (Kamel and Eid 2005).

The Mediterranean Sea, a semi closed basin connected to the Atlantic Ocean through Gibraltar Strait in its western extremity, exhibits an annual net heat loss of approximately 5 W/m^2 (MacDonald et al. 1994) and a net freshwater loss of approximately 60 cm (Song and Yu, 2017). Results of previous research revealed that almost 90% of the heat and freshwater losses in the Mediterranean basin are balanced by the inflowing fresh Atlantic waters through the Strait of Gibraltar (Baschek et al. 2001). The remaining 10% of freshwater loss is compensated by discharges from rivers, e.g., the Nile (Struglia et al. 2004). The heat content is considered an accurate component to investigate the likely thermal cyclic behaviour within a specific basin; because it allows for the elimination of diurnal (full) and to a lesser extent monthly effects on the examined thermal behaviour. The temperature and salinity trends of variations over 30 years, as described in the Mediterranean by Levitus et al. (2005), have substantially reversed since the mid-1990s in line with the variations in the phases of the North Atlantic Oscillations (NAO). This reflects a mark of a cyclic behaviour of variation.

The Mediterranean basin is divided by the Strait of Sicily into the western Mediterranean basin and the eastern Mediterranean basin (Figure 1). The latter comprises four sub basins, namely: Ionian, Levantine, Aegean and Adriatic. The Levantine basin is southerly bordered by the Egyptian Mediterranean Coast, which extends between 30.0° to 33.0° N and 24.5° to 36.0° E (Figure 2). The HS in the eastern Mediterranean basin has been previously investigated.

Figure 1. *The Mediterranean Sea with its Two Wings: Western and Eastern Basins*

Source: Authors.

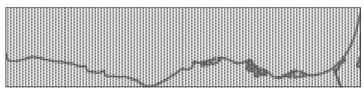
The HS along the eastern side of the Levantine results from the sun-air-sea radiation balance, and the dominant west-east wind pattern (Tzvetkov and Assaf 1982). Results of Maiyza (1993) revealed that March is the month of the minimum HS in the eastern Mediterranean basin, whereas the maximum occurred respectively in August and September for the 100 and 300 m layers. In the Eastern Mediterranean basin, the amount of HS is generally higher in the Levantine. Houpert et al. (2015) declared that the anticyclonic and cyclonic gyres in the Eastern Mediterranean basin play a significant role in the spatial and temporal variability of its heat storage rates. Kamel et al. (2020) concluded that the upper 100 and 300 m layers in the Eastern Mediterranean basin exhibit a maximum HS in the southern and south-eastern parts throughout the period August-October, while the minimum values of HS are founded in the northern part during February-March. From 1993 to 2019, the averaged heat content anomaly (0-700 m depth layer) displayed an annual trend of 1.4±0.3 Wm^{-2} (Kubin et al. 2023). Maiyza et al. (2023) confirmed the occurrence of the 70-year cycle of variation in the hydrographic conditions in the Levantine Basin, taking the HS parameter as examined parameter, for an extended time series records of temperature and salinity (1965-2021).

This study aims to better understand the monthly and annual behaviour of changes in the HS in the south-eastern Mediterranean basin, and to calculate the heat storage index for its upper 100 and 300 m layers. The objectives of the study can be pointed out as: (1) To examine the monthly mean trends and behaviour of the HS at the 100 and 300 m layers; (2) To examine the annual mean trends and behaviour at the same layers and (3) To calculate the HS index at the two layers.

Data and Methods of Analysis

The present area of interest is the southern Levantine basin, off the Egyptian Mediterranean Coast (Figure 2). This extends from the northern coastline of Egypt to 33°N and from 25°E to the Asian shore.

Figure 2. *The Levantine Basin with the Area of Investigation Shaded*



Source: Authors by using Surfer16® Software.

For the years 1948–2021, the hydrographic data -temperature and salinity- were dispersed monthly. The World Data Centres (WDC) A (Washington) and B (Moscow), the Egyptian National Oceanographic Data Centre (ENODC), and the

Russian cruises through the Physical Oceanography of Eastern Mediterranean (POEM) project were the sources of the data. The upper 300 meters, which represent the surface, subsurface, and upper part of the intermediate water mass in the Eastern Mediterranean basin, were taken into consideration for their monthly heat storage (Maiyza 1993). The 100 and 300 m layers are the focus of this study on a monthly and annual basis.

The integrated monthly heat storage was calculated using the following equation:

$$h = \int_0^z \rho \, C_p \, T dZ \tag{1}$$

where,

h is the monthly heat storage (Jm^{-2})
ρ is the mean seawater density (kgm^{-3})
C_p is the mean specific heat capacity ($Jkg^{-1}C^{-1}$)
T is the mean seawater temperature (°C)

The specific heat capacity was calculated using the following equation (Korne 1972):

$$C_p = 4186\,[1.0049 - 0.001621\,S + (3.5261 \times 10^{-6}\,S^2) - \{(3.2506 - 0.1479\,S + 7.7765 \times 10^{-4} S^2)10^{-4} T\} + \{(3.8103 - 0.12084\,S + 6.121 \times 10^{-4} S^2)10^{-6} T^2\}] \tag{2}$$

The integrated monthly heat storage anomaly was calculated as:

$$\Delta h = h - h_m \tag{3}$$

where,

Δh is the mean monthly heat storage anomaly (Jm^{-2})
h is the calculated monthly heat storage using Equation (1)
h_m is the climatologic heat storage over a specific month (Jm^{-2}).

Based on the obtained monthly results, the annual mean heat storage was calculated. The trends of variations in the mean HS, on monthly and annual basis, were examined using both linear and quadratic regression approaches. The rates of variations and the years of minimum occurrence were specified at the two layers of interest. The significance of the obtained annual linear trends was assesses using the non-parametric Mann-Kendall test.

The seasonal index is a crucial tool for analyzing seasonal fluctuations in any phenomenon that is being investigated and changes often for less than a year (Maiyza and El-karyoney 2020). A base value of 100 percent is used to determine the seasonal index of the used data (Welsh et al. 2011). This is achieved by following steps (Carbunaru and Bacescu 2013): To represent only monthly seasonality variations, the monthly average values are calculated in step 1. In step 2, the estimated value is calculated for each month using a linear time trend equation derived from the monthly average values data. In step 3, the true value is divided by the estimated value for each month (%). Therefore, the seasonal index of HS at the two considered layers (100 and 300 m) was calculated and presented:

Seasonal index = Mean HS / Typical directional value * 100 (4)

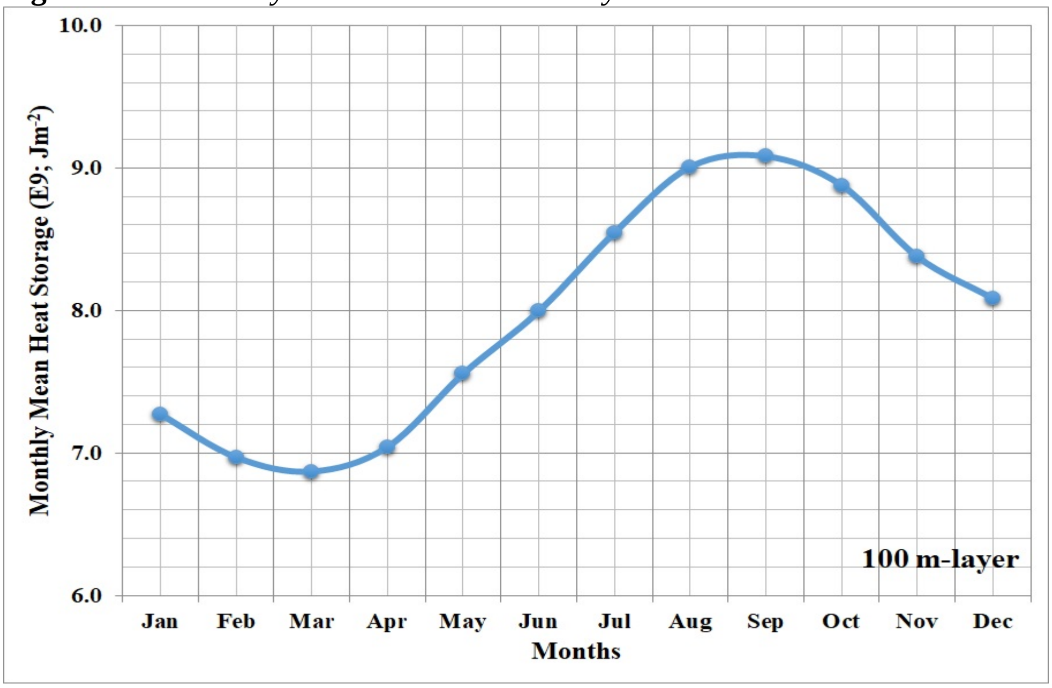
The linear regression approach was used to test the HS trends of variations.

Results

Monthly Mean Heat Storage

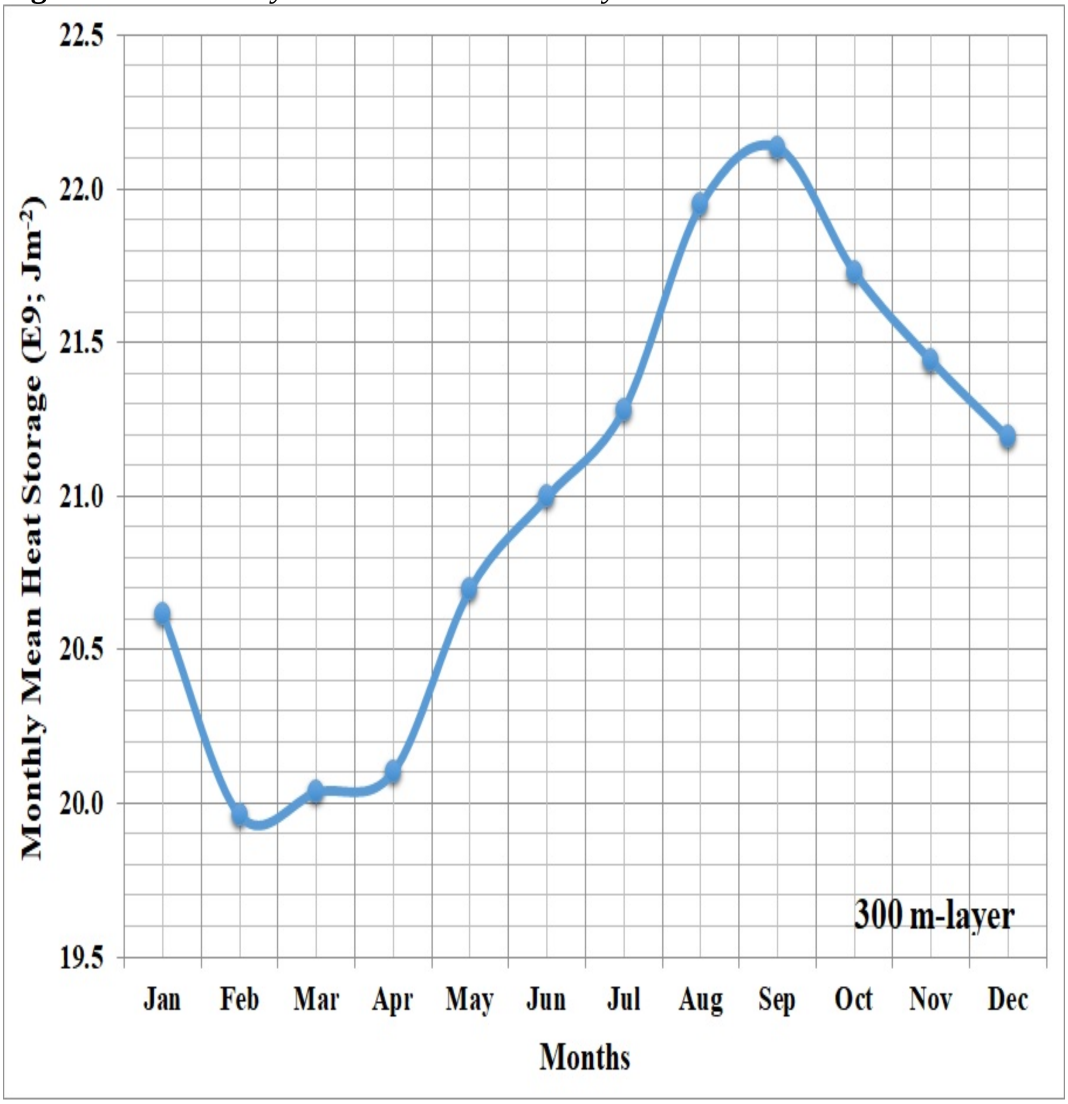
The monthly mean HS varied between 6.86E9 Jm^{-2} (March) and 9.08E9 Jm^{-2} (September), with an average of 7.97E9 Jm^{-2}, at the 100 m-layer (Figure 3). At the 300 m-layer, the monthly mean HS variated between 19.96E9 Jm^{-2} (February) and 22.134E9 Jm^{-2} (September), with an average of 21.011E9 Jm^{-2} (Figure 4).

Figure 3. *The Monthly Mean HS at the 100 m-layer*



Source: Authors

Figure 4. *The Monthly Mean HS at the 300 m-layer*



Source: Authors

Annual Mean Heat Storage

At the upper 100 m-layer, the annual mean HS (Figure 5) variated between 7.03E9 Jm^{-2} in 1992 and 8.72E9 Jm^{-2} in 1955, with an overall annual mean HS of 5.69E9 Jm^{-2} throughout the period of investigation. The annual mean HS at the upper 300 m-layer (Figure 6) fluctuated between 19.64E9 Jm^{-2} in 1992 and 21.98E9 Jm^{-2} in 1948, with an overall annual mean of 20.98E9 Jm^{-2} over the period 1948-2021. The annual mean HS at the two layers of consideration had decreasing linear trends, with different rates over the period of investigation. These rates were -3.94E6 Jm^{-2}/yr and -0.0037E9 Jm^{-2}/yr, respectively at the 100 m and 300 m layers. The two liner model equations that represent these decreasing trends at the 100 m and 300 m layers are respectively as follows:

$$y = -4E{+}06\ x + 2E{+}10;\ r = 0.30 \qquad (5)$$

$$y = -0.0038\ x + 28.492;\ r = 0.14 \qquad (6)$$

Furthermore, the quadratic regression models reveal that the annual mean HS at the two layers of interest tend to exhibit a cyclic behaviour of changes over the period of investigation. This is represented by the following Equations:

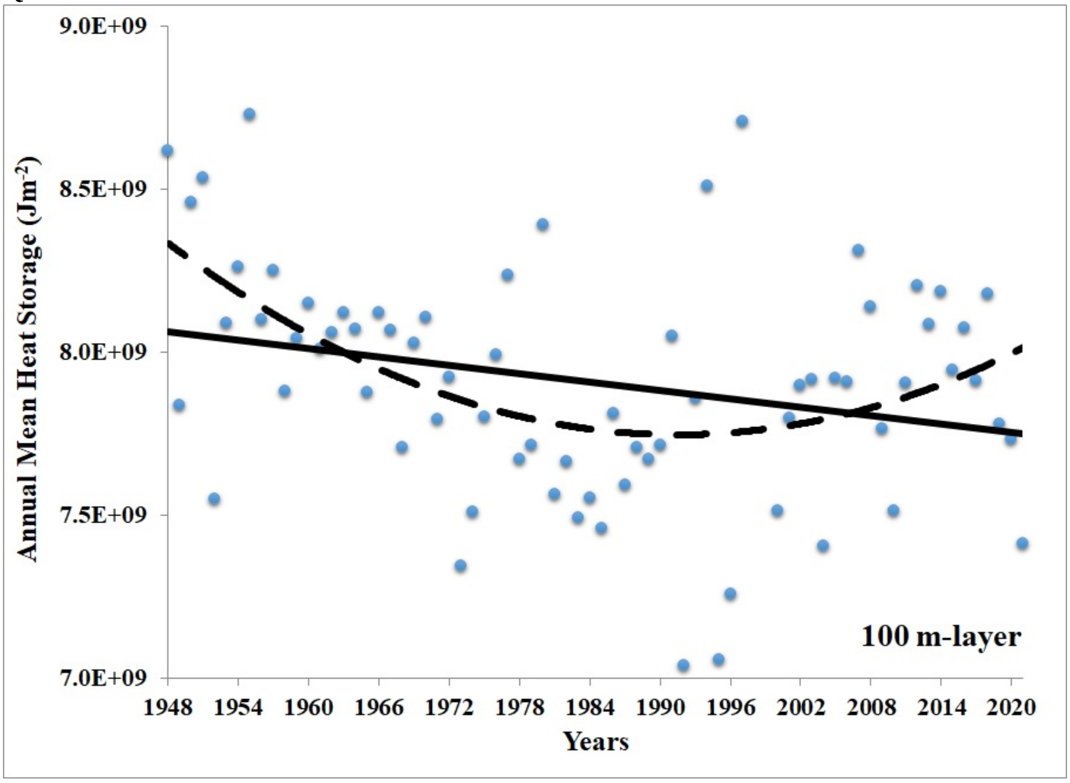
At the 100 m-layer: $y = 309600\ x^2 - 1.2332E{+}09\ x + 1.2357E{+}12;\ r = 0.45$ (7)

At the 300 m-layer: $y = 0.00065178\ x^2 - 2.5938\ x + 2601.2;\ r = 0.50$ (8)

These parabolas show a decrease in the annual mean HS from 1948 to 1992 (100 m-layer) and 1989 (300 m-layer), followed by an increase afterward.

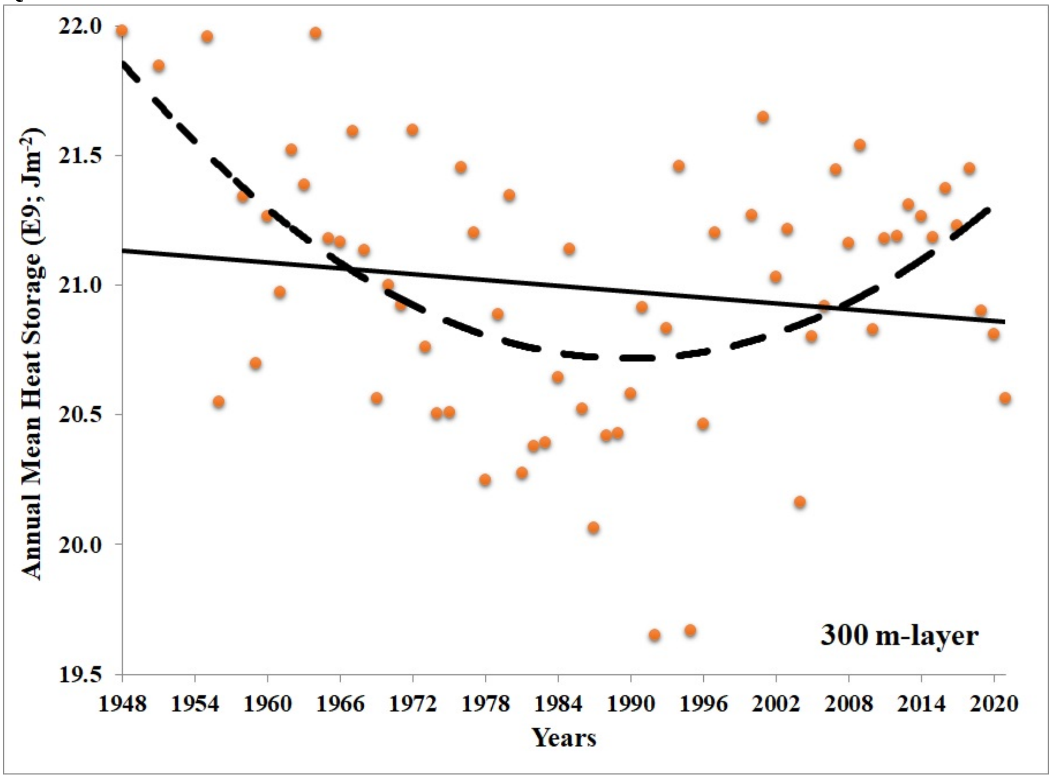
The results of the Mann-Kendall test assessing the obtained annual trends at the two layers of interest are shown in Table 1. It is obvious that the decreasing trend at the 100 m-layer is more significant than that obtained at the 300 m-layer. This is consistent with the above mentioned rates at the two layers.

Figure 5. *The Annual Mean HS at the 100 m-layer, and its Annual Linear and Quadratic Trends*



Source: Authors

Figure 6. *The Annual Mean HS at the 300 m-layer, and its Annual Linear and Quadratic Trends*



Source: Authors

Table 1. *Mann-Kendall Test Results*

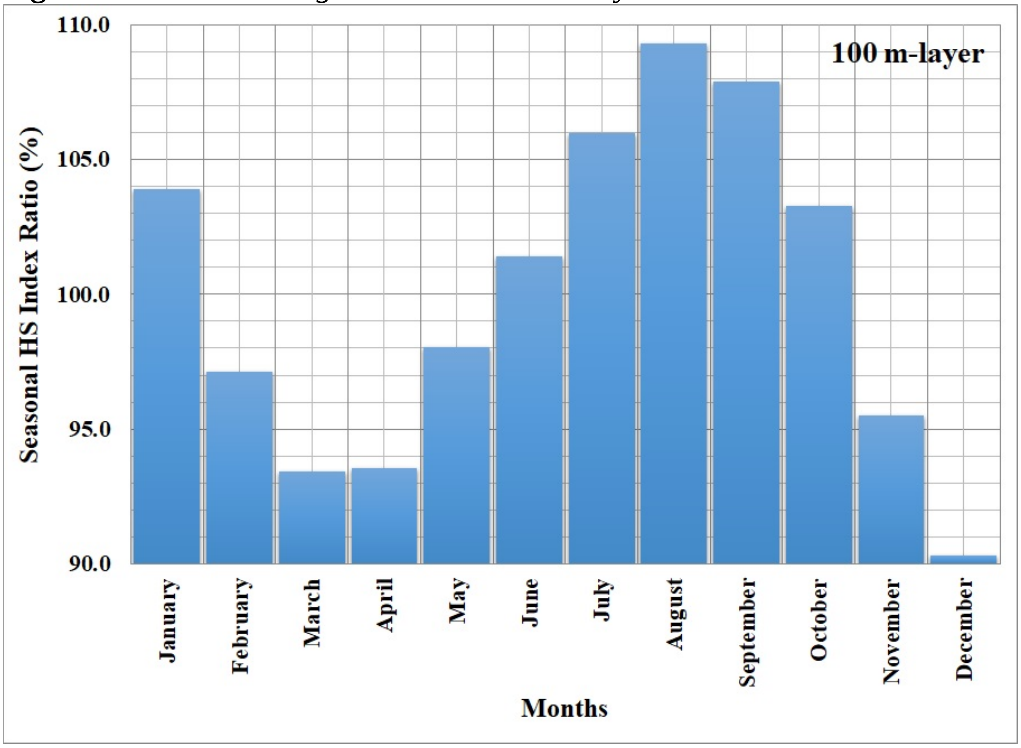
	100 m –layer Trend	300 m-layer Trend
S	-527	-144
Z	-2.50	-0.07
Trend	Decreasing	Decreasing
Significance (0.05)	*	---------

Source: Authors.

Heat Storage Index

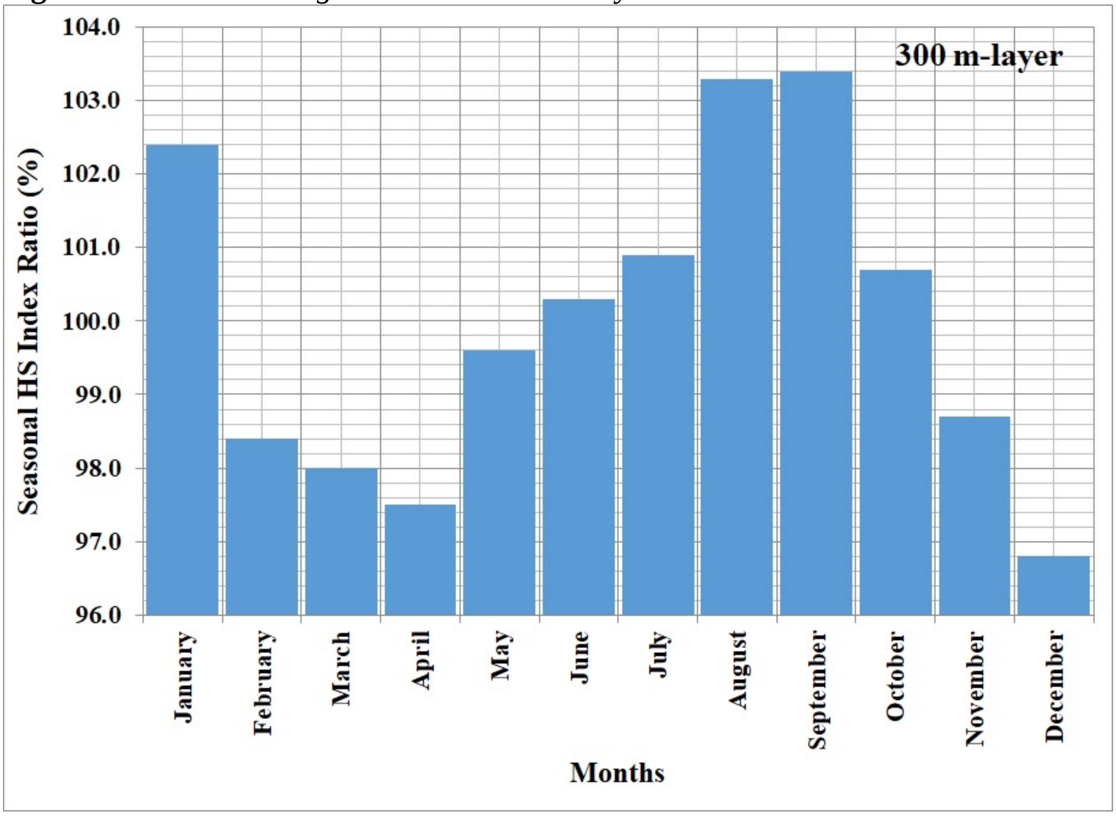
Figures 7 and 8 show the seasonal index of HS at the 100 m and 300 m layers, respectively. The two indices show that the seasonal index follows the mean monthly HS patterns of variations at the two layers for maxima, but differ for the minima. At the 100 m-layer, the minimum index appeared in December (90.3%), and the maximum in August (109.3%). At the 300 m-layer, the minimum index appeared also in December (96.8%), and the maximum in September (103.4%).

Figure 7. *The Heat Storage Index at the 100 m-layer*



Source: Authors

Figure 8. *The Heat Storage Index at the 300 m-layer*



Source: Authors

Discussion

The long-term variations in the south-eastern Mediterranean temperature and salinity were previously studied. This comprises the work of (Maiyza and Kamel 2009, 2010, Maiyza et al. 2010, El-Geziry et al. 2019, El-Geziry 2021). As the heat storage (HS) at the different depth-levels depends mainly on these two parameters (Equation 2), it will be affected by their variations on a spatiotemporal scale.

Results revealed that the heat content in the south-eastern Mediterranean region reached its minimum values from February to April, and its maximum from August to October. This is in agreement with the conclusion of Maiyza (1993) who declared March as the month of minimum HS in the south-eastern Mediterranean region, and August and September as moths of maximum at the 100 and 300 m-layers, respectively. Also, Kamel et al. (2020) declared that the highest and lowest values of HS in the upper 100 and 300 m layers in the eastern Mediterranean basin, respectively, occur between the end of the heating season (August-October), and the end of the cooling season (February-March).

Maiyza and Kamel (2009) examined the sea surface temperature (SST) variations on both monthly and annual basis in the south-eastern Mediterranean region throughout the period 1948-2008. They concluded a SST decreasing trend of -0.004°C/yr over this period. They also concluded a cyclic behaviour in the observed variations, using the quadratic regression approach. This cycle had its lowest value in 1985. The same conclusion was declared by Levitus et al. (2005) for the entire Mediterranean basin throughout the period 1970-2000, with 1980 being the year of minimum SST occurrence. These oscillations in the south-eastern Mediterranean basin were said to vary between 8 and 15 years, almost associated with the 11 year cycles of sun spot activities (Maiyza et al. 2010). Maiyza and Kamel (2010) investigated the long term variations in the surface salinity of the south-eastern Mediterranean basin over the period 1948-2010. They concluded a linear increasing trend with a rate of +0.003/yr. Their results of quadratic regression approach revealed a cyclic behaviour in the change of the surface salinity, with a decrease from 1948 to 1980 followed by an increase afterward. An increasing trend in the seawater salinity at the 100 m-layer in the south-eastern Mediterranean basin was concluded by El-Geziry et al. (2019), with a rate of +0.0003/yr over the period 1948-2012. They also revealed that at this layer the quadratic approach reflected an increase from 1948 to 1984 followed by a decrease afterward. At the 300 m-layer, they concluded a linear increasing trend of +0.01/yr, and declared 1972 as year of minimum salinity occurrence by using the quadratic regression approach. The southern Levantine basin exhibited an increasing SST with a rate of +0.04°C/yr over the period 1948-2018 (El-Geziry 2021). However, the SST had a decreasing trend with a rate of -0.06°C/yr (1975-1991) and an increasing trend (+0.2°C/yr) from 2002 to 2018, which reflects the influence of climate change in this region. Many research have assessed the heat content in oceans and its variations over different time spans. Results revealed that this content exhibits cyclic variations (Levitus et al. 2000, 2005, Domingues et al. 2008, Kamel et al. 2020, Maiyza et al. 2023). The present results revealed that the heat content over the period 1948-2021 at the two examined layers (100 m and 300 m) exhibited decreasing trends. This is in contrast to the results of El-Geziry et al. (2021) who showed opposite increasing trends in the seawater temperature in the same region at the same two layers over the period 1948-2012. While the present study showed a rate of -3.94E6 Jm-2/yr and -0.0037E9 Jm-2/yr, respectively at the 100 m and 300 m layers, El-Geziry et al. (2021) calculated increasing rates of +0.02°C/yr and +0.002°C/yr respectively at the 100 m and 300 m layers. This opposition between the temperature property and heat content at the two layers of concern may be attributed to the difference in the span of examination between the two studies. On the other hand, using the quadratic approach, results revealed a cyclic behaviour of change in the heat content, with a minimum year of occurrence in 1992 at the 100 m-layer and in 1989 at the 300 m-layer. This is in agreement with the conclusions revealed by El-Geziry et al. (2021) for the subsurface temperature variations in the same region for the same layers. However, while 1989 is close to the 1987 by El-Geziry et al. (2021) for the 300 m-layer, the minimum year of occurrence for the subsurface temperature at the 100 m-layer was 1981. This retard in the calculated minimum year of occurrence at the 100 m-layer between the temperature (1981) and the heat content (1992), may be attributed the convection and mixing processes dominating the upper layer in the Mediterranean region. Just beneath the surface Atlantic waters, the Eastern Levantine Intermediate Water (ELIW) mass may be easily followed up to Gibraltar. It is the warmest and saltiest mass generated in the entire Mediterranean basin (El-Geziry 2010, El-Geziry and Bryden 2010). This ELIW mass does, in fact, reach the deep water formation zones of the basin during its spreading phase, and its high salinity (39) contributes to the preconditioning of the water column (Drakopoulos and Lascaratos 1999). This may explain the very close year of minimum occurrence between the present study (1989) and that calculated by El-Geziry et al. (2021) (1987) for the 300 m-layer.

The HS seasonal index in the south-eastern Mediterranean region was calculated for the first time in this study. Therefore, there is no reference to base the obtained results. The present results showed that the maximum HS index, at the two layers of interest, coincides with the maximum mean monthly HS (August and September). However, the lowest index occurred in December, and not in March.

As a direct application and interconnection between the variations in the seawater temperature and salinity, main parameters affecting the HS, and the total catch in the south-eastern Mediterranean Sea, El-Geziry et al. (2013) concluded positive correlations between the hydrographic parameters and the total catch, with a special impact for the sea surface salinity. This correlation between the heat content itself and the total catch in the region need further investigation to reach a robust conclusion about this relationship.

Conclusion

To conclude, the heat storage in the south-eastern Mediterranean region is said to exhibit cyclic trend of variations over time spans at the different water layers. However, the period of this cycles that can be detected vary according to the investigated layer. This may be attributed to both the dynamical processes taken place at each layer and to the criteria of the water masses spreading over the different depths in the south-eastern Mediterranean region.

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Research on GNSS-PWV Retrieval and its Application in Rainfall Forecasting Based on Deep Learning

By Xiangrong Yan[*], *Weifang Yang*[±], *Yuzhao Li*[°], *Xiaoning Su*[•], *Liming Zhang*[♦] *& Xiaomin Lu*[♥]

This thesis mainly studies the state-of-the-art methods and models of Precipitable Water Vapor (PWV) derived from ground-based Global Navigation Satellite Systems (GNSS) and its applications in rainfall forecast. Firstly, Convolutional Neural Networks (CNN) is utilized for feature extraction from GNSS-PWV data, leveraging their powerful image processing capabilities to identify spatial features in PWV. Subsequently, the Autoregressive Integrated Moving Average (ARIMA) model is applied for time series analysis, capturing the temporal dependencies in PWV variations. To further enhance the time series prediction performance, Long and Short Term Memory Neural Network (LSTM) is introduced to handle the long-term and short-term dependencies in PWV data, addressing the limitations of traditional time series models. Additionally, attention mechanisms are integrated into the LSTM models to improve their focus on critical time steps, thereby increasing prediction accuracy. To optimize the model parameters, the Slime Mold Algorithm (SMA) is employed. SMA, a novel optimization algorithm inspired by the foraging behavior of slime mold, efficiently searches for optimal solutions in high-dimensional spaces, thereby enhancing the convergence speed and prediction accuracy of the models. Experimental results demonstrate that the models integrating multiple deep learning techniques perform excellently in GNSS-PWV retrieval and rainfall forecasting, significantly outperforming single models.

Keywords: *global navigation satellite system, precipitable water vapor, rainfall forecasting, deep learning*

[*]Graduate Student, 1st Faculty of Geomatics, Lanzhou Jiaotong University, 2nd Nation-Local Joint Engineering Research Center of Technologies and Applications for National Geographic State Monitoring, & 3rd Gansu Provincial Engineering Laboratory for National Geographic State Monitoring, China.

[±]Professor, 1st Faculty of Geomatics, Lanzhou Jiaotong University, 2nd Nation-Local Joint Engineering Research Center of Technologies and Applications for National Geographic State Monitoring, & 3rd Gansu Provincial Engineering Laboratory for National Geographic State Monitoring, China.

[°]Associate Professor, 1st Faculty of Geomatics, Lanzhou Jiaotong University, China.

[•]Professor, 1st Faculty of Geomatics, Lanzhou Jiaotong University, China.

[♦]Professor, 1st Faculty of Geomatics, Lanzhou Jiaotong University, China.

[♥]Associate Professor, 1st Faculty of Geomatics, Lanzhou Jiaotong University, China.

Introduction

With the intensification of global warming, the frequency and intensity of extreme weather events such as heavy rainfall will further increase (IPCC 2021, Zhang 2015), which will bring about serious catastrophic consequences such as floods, landslides, mudslides, and so on, and therefore, it is an urgent and realistic challenge to carry out heavy rainfall forecasting and early warning.

The main material basis for the formation of heavy rain is atmospheric water vapor, therefore, effective monitoring and scientific analysis of atmospheric water vapor content, as well as reliable forecasting models are the key to achieve accurate forecasting of catastrophic weather such as heavy rain, and also an important guarantee to enhance the emergency response capability of disaster prevention and mitigation. Atmospheric water vapor information can be obtained by means of high-altitude radio sounders, solar photometers, water vapor radiometers, satellite remote sensing and ground-based GNSS inversions. Among them, the quantitative parameter of ground-based GNSS inversion of water vapor is Precipitable Water Vapor (PWV) in the atmosphere, and GNSS PWV has the advantages of all-weather, low cost, high accuracy, and high temporal resolution (Ware et al. 1993, Yao et al. 2017). Therefore, high-precision, high temporal and spatial resolution PWV has a very important social value for rainfall and extreme weather forecasting.

PWV fluctuates quickly and exhibits clear nonlinearity, nonstationarity, and randomness due to complex causes (Sharifi and Souri 2014), which has become a difficult point to accurately predict PWV. The current difficulty is how to adopt PWV forecast models that are more stable, accurate, and dependable. Three basic categories can be used to categorize current prediction models: integrated models, independent artificial intelligence models, and classic statistical models. Deep learning models can be introduced to improve computational efficiency and prediction accuracy for nonlinear systems with large and complex data volumes (Borhani-Darian et al. 2023, Han et al. 2022). Studies have shown that separate artificial intelligence models have disadvantages such as simple algorithms and local optimization prone to overfitting phenomenon, resulting in poor prediction accuracy, so combined models can be introduced.

In summary, water vapor plays an important role in the atmosphere, and its changes have a significant impact on meteorology and climate. Meanwhile, PWV is a key factor in the occurrence of rainfall events, and high temporal and spatial resolution, all-weather monitoring of PWV can help to reveal the mechanism of extreme weather generation, evolution and extinction, and provide a strong scientific basis for improving the forecasting accuracy. Therefore, this study aims to address the challenges of GNSS PWV inversion and rainfall forecasting by adopting deep learning algorithms to investigate a high-precision real-time PWV inversion method, to realize the high spatial and temporal resolution monitoring of water vapor, to reveal the response mechanism of multidimensional PWV during rainfall formation, and to put forward a high-precision rainfall short-term proximity warning method, so as to improve the knowledge and understanding of rainfall events, and to enhance the disaster prevention and mitigation capabilities.

Literature Review

With the rise of machine learning technology in recent years, especially the rapid development of computer vision, many scholars have utilized deep learning methods to carry out applied research on rainfall forecasting. The current PWV prediction models are mainly categorized into 3 types: traditional statistical models, separate AI models, and combined or hybrid models. Among them, both separate AI models and combined models belong to deep learning models. Statistical models mainly include exponential smoothing (ES), autoregressive (AR), moving average (MA), and Autoregressive Integrated Moving Average (ARIMA). Manandhar et al. (2019) used the ES algorithm to predict missing PWV values and discovered that the system performed well in identifying seasonal fluctuations in PWV levels. Acheampong and Obeng (2019) predicted PWV models in West Africa using AR, ES, MA, and ARIMA. The results demonstrated the excellent prediction accuracy of autoregressive models. However, statistical models are poor at capturing nonlinear interactions because they are predicated on the idea that time series have a linear structure (Wang et al. 2017). Individual artificial intelligence models include Artificial Neural Network (ANN), Backpropagation Neural Network (BP), Convolutional Neural Network (CNN), Wavelet Neural Network (WNN), Support Vector Machine (SVM), Long and Short Term Memory Neural Network (LSTM), and Gated Recurrent Units (GRU). Senkal et al. (2011) utilized the ANN method to predict the PWV in Cukurova area and found that the predicted PWV values were closer to the sounding observations. Hao-Bo Li (2021) constructed a multi-parameter rainfall forecasting model for Hong Kong region using BP model and achieved accurate prediction of rainfall events. Pan et al. (2019) used CNN to improve the precipitation prediction model. Ge et al. (2015) found that the prediction results and accuracy of the WNN model were significantly better than that of BP in the prediction of the precipitable amount of rainfall. Manandhar et al. (2019) used SVM method to analyze the various factors affecting atmospheric precipitation and found that elements such as temperature, relative humidity, dew point temperature, solar radiation, and PWV play an important role in rainfall. It was found that LSTM showed better performance compared to ARIMA model for long term prediction in drought areas. Individual AI models also have some problems, such as simple algorithms, easy to fall into the local optimum and overfitting phenomenon. Since individual AI models have limitations including overfitting, a poor convergence speed, and a propensity to fall into local optimization, they are not always practical. Given that individual models frequently lack the capacity to fully capture high-frequency mutation points and nonlinear trends in PWV, Bates and Granger (1969) presented a combination model whose primary function is to integrate and deconstruct in order to combine the benefits of many prediction models. (Xiao et al. 2022) broke down the water vapor data series using the full empirical modal decomposition of adaptive noise, and then used an ARIMA-LSTM combination model to forecast the PWV, which resulted in a 30% reduction in the post-computational error term compared to an individual LSTM model. In 2019, Yue and Ye (2019) utilized the ANN and genetic algorithm to predict the PWV at Zhongshan Station in

Antarctica for 6 h and 12 h. (Shang et al. 2023) combined wavelet analysis, LSTM, and ARIMA for GNSS PWV prediction, and the results showed that the R^2 of PWV predicted by the model were all above 0.95. The prediction accuracies of these combined models are significantly higher compared to traditional statistical models and individual AI models. Although there are fewer types of combination models and fewer researchers have used intelligent optimization algorithms to determine the weight coefficients of model combinations, the studies mentioned above demonstrate that the rainfall prediction combination models' prediction accuracy is significantly better than that of individual artificial intelligence models and traditional statistical models.

Methodology

Convolutional Neural Network (CNN)

There are two types of convolutional layers in CNN model, one-dimensional convolution and two-dimensional convolution. Among them, one-dimensional convolution is mostly applied to time series data and two-dimensional convolution is mostly applied to image data. The convolutional layer performs discrete convolution operations on the input data according to equations (1) and (2) as a way to extract spatial features of the input data.

$$y_{i,j} = \sigma(W_k \otimes x_{i,j} + b_k) \qquad (1)$$

$$W_k \otimes x_{i,j} = \sum_{m=0}^{a-1}\sum_{n=0}^{b-1} w_{m,n} \times x_{i+m,\, j+n} \qquad (2)$$

where $x_{i,j}$ and $y_{i,j}$ are the input data and output data of the convolutional layer, respectively; $\otimes$ is the discrete convolution operation; W_k and b_k are the weight and bias of the kth convolutional kernel, respectively; σ is the activation function of the neuron; a and b are the size parameter of the convolutional kernel.

The CNN used in this study is a one-dimensional convolution, and the principles are briefly summarized below. In one-dimensional convolution, the height of the convolution kernel can be set according to the demand, while the width of the convolution kernel is the same as the number of columns of the time series. In the process of convolution, the convolution kernel is first convolved with the time series from top to bottom, and then the result of the convolution is added with the bias and then passed through the activation function, and finally the output convolution result is sent to the next layer.

Autoregressive Integrated Moving Average (ARIMA)

Autoregressive integrated moving average (ARIMA) model is expressed as ARIMA (p, d, q), the process of identifying and defining the order of ARIMA model can be regarded as the process of determining the three parameters of p, d

and q. The number of differences d can be determined in the process of time series data smoothness test and smoothing. The smoothing procedure and time series data smoothness test can be used to calculate the number of differences d, d is a non-stationary series into a smooth series needs to be the number of differences, after the formation of the difference of the smooth time series can be modeled using the ARIMA model. In the ARIMA modeling process, the order p of autoregression and the order q of moving average should be determined according to the autocorrelation coefficient, partial autocorrelation coefficient, autocorrelation function and partial autocorrelation function graph.

(1) Data smoothness detection. Test whether the time series data is smooth, non-smooth data will lead to the ARIMA model prediction effect is reduced, need to use the method of n-order difference on making the time series become smooth.

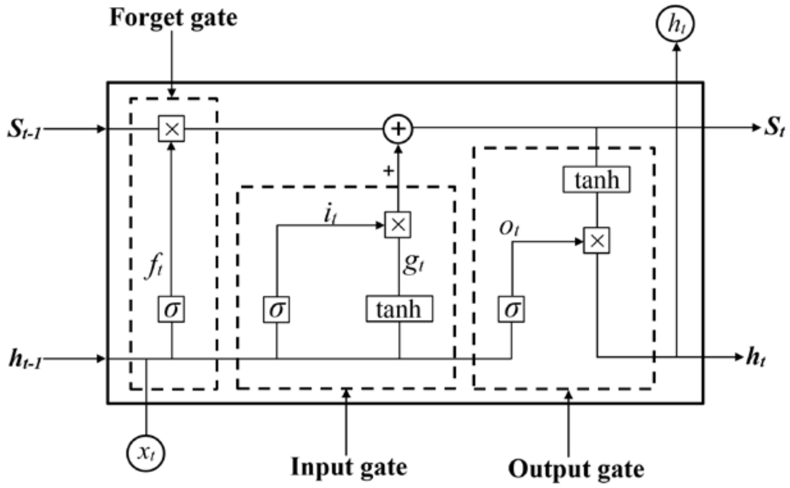
(2) Model parameterization. Autocorrelation and partial autocorrelation analysis of the time series, the model parameters p, q will be determined by analyzing the results of the autocorrelation and partial autocorrelation analysis of the image analysis and combining the Bayesian Information Criterion and Akaike Information Criterion to determine.

(3) Residual testing. After the model parameters are determined, the fitting effect of the model is tested, and if the fitting effect is not good, the parameters are re-determined by repeating the above step mule. The ARIMA model has a better effect on linear data processing and a poor effect on non-linear data processing, and the LSTM model has a strong learning ability for data with strong non-linear characteristics, thus the LSTM model is introduced to predict the non-linear data in order to improve the performance of the ARIMA model on non-linear data, and to improve the performance of the ARIMA model on non-linear data to improve the prediction effect of ARIMA model for GNSS water vapor.

Long and Short Term Memory (LSTM)

Long and Short Term Memory (LSTM) is a neural network for processing temporal data, first proposed by Schmidhuber and Hochreiter, which can solve the problem of gradient explosion and gradient disappearance that occurs easily in the training process of RNN neural networks. Compared to recurrent neural networks, LSTM introduces long-term memory cell states and uses a "gate" structure to control the states and outputs at different moments. Therefore, LSTM neural network has very important research value and application prospect in time series prediction. Figure 1 depicts the LSTM neural unit's construction.

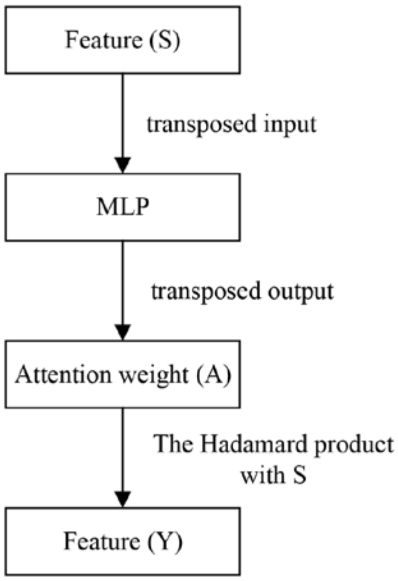
Figure 1. *Structure of LSTM Neural Unit*



Attention Mechanism

The core idea of Attention Mechanism is to simulate the process of human's attention allocation when processing information, and its essence is to make the model focus on valuable information and filter out irrelevant information, so as to extract key features from a large amount of information. The computational flow of the attention mechanism is shown in Figure 2. The feature input is transposed into the Multi-Layer Perceptron, after which the transposed output calculates the resultant attention weights. Subsequently, the attention weights are made Hadamard product with the feature inputs, that is matrix pairwise multiplication, to obtain the feature output after the allocation of attention weights.

Figure 2. *Flowchart of Attention Mechanism Calculation*



Slime Mold Algorithm (SMA)

Slime Mold Optimization Algorithm (SMA) is an emerging nature-inspired optimization algorithm inspired by the behavior of slime molds in their search for food. Slime molds are unicellular organisms that explore their environment by moving and expanding their pseudopods and searching for food sources. The SMA algorithm simulates this process to find the global optimal solution through cooperative and competitive mechanisms. The core of the SMA algorithm is to simulate the foraging behavior of the slime molds in the natural environment. When searching for food, the slime mold releases chemicals to attract other slime molds to move towards the food source, and adjusts its path to find the optimal path for food acquisition.

This process can be divided into the following stages:

(1) Initialization: a group of slime mold individuals are randomly initialized in the search space, each representing a potential solution. The location and number of initial individuals are determined by the dimension of the problem and the extent of the search space.
(2) Adaptation evaluation: Evaluate the adaptability of the position (solution) of each slime mold individual according to the objective function, i.e., the quality of the solution. The higher the fitness of an individual, the closer its position is to the optimal solution.
(3) Position update: The slime mold individual updates its position according to its own fitness and that of other individuals, as well as the concentration of chemotaxis substances.
(4) Pheromone update: The chemotaxis concentration is updated according to the individual fitness. Regions with high pheromone concentration attract more slime mold individuals, which increases the probability of finding the optimal solution in that region.
(5) Iteration: Repeat the process of fitness evaluation, location updating and pheromone updating until a predetermined number of iterations is reached or a convergence condition is satisfied.

In conclusion, the slime mold optimization algorithm provides an innovative and effective optimization method by simulating the foraging behavior of slime molds in nature, which is widely used in various complex optimization problems. Its global search capability and flexible adaptability make it show a broad application prospect in many fields.

Construction of the Model

In this study, a combined SMA-CNN-ARIMA-LSTM-Attention model combining SMA algorithm, CNN network, ARIMA model, LSTM network and attention mechanism is constructed.

Firstly, the parameters of SMA algorithm are set to randomly generate initial individuals and update the parameters according to the algorithm formula. In the input layer, the input data is a time series of $x_{n,p}$ containing multiple features, which is a two-dimensional matrix composed of historical data from multiple monitoring points, with one row representing the monitoring values of p monitoring points for the same period, and one column representing the n-period monitoring data of a single monitoring point.

Secondly, the multidimensional time series after data preprocessing is input into the CNN network for convolution operation to extract the spatial features between the target monitoring point and the neighboring monitoring points to obtain the multi-feature time series data.

Thirdly, wavelet analysis is used to separate the multidimensional feature sequence generated by the CNN layer into low-frequency and high-frequency components. The ARIMA model predicts the low-frequency components to deal with the linear part of the water vapor data. The LSTM-Attention model predicts the high-frequency components to deal with the nonlinear part of the water vapor data.

Fourthly, the data obtained from the two models are summed to obtain the final water vapor prediction. Through the fully connected layer, the predicted values of the target monitoring points are integrated and output.

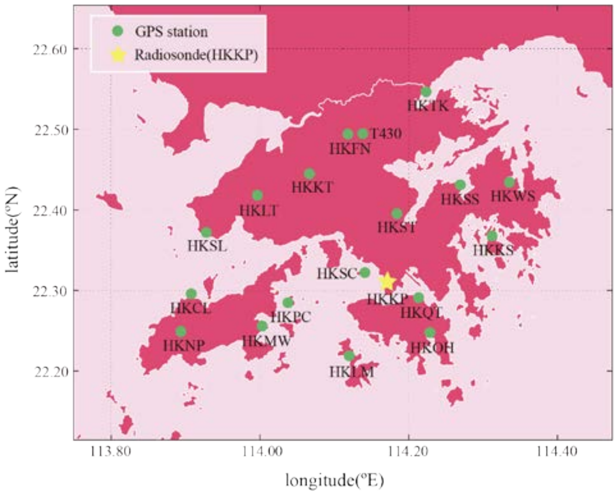
Finally, the fitness of the hyperparameter combination corresponding to the current individual is calculated and the optimal individual is recorded. Should it be determined that the algorithm has not completed the allotted number of iterations, the parameters are updated according to the SMA algorithm formula, and the data are re-input with the new hyperparameter combination for model training and testing. If the algorithm reaches the maximum number of iterations, the hyperparameter combination corresponding to the optimal individual is output and substituted into the model for retraining and testing to obtain the hyperparameter optimized SMA-CNN-ARIMA-LSTM-Attention model.

Results

Study Area

In this study, the Hong Kong region was selected as the study area, with the latitude and longitude ranging from 113º48'~114º24'E and 22º6'~22º36'N, as shown in Fig.3. The Hong Kong region is located in the south of China, in the Pearl River Delta, east of the South China Sea and northwest of Guangdong Province. There are four different seasons in the subtropical monsoon climate of the region, with hot and humid summers and relatively cooler and drier winters. We collected daily hourly GNSS data from January to August 2022 as the study object, and predicted the data in July and August, while the HKKP station was selected as the target monitoring station.

Figure 3. *GNSS Station Location in Hong Kong*



Data Processing

In this study, GNSS observations were processed using GAMIT 10.71 software to obtain the water vapor observations PWV, and the solution strategy is shown in Table 1.

Table 1. *Calculation Strategy of GAMIT 10.71*

Parameter name	Parameter setting
Data sampling interval /s	300s
Time resolution /h	2h
Cutoff altitude angle /°	10°
Mapping function model	VMF1
Tide correction model	otl_FES2004
Tropospheric delay model	Saastamoinen
Ionosphere model	NONE
IGS Auxiliary Stations	GUAM, POL2, USUD

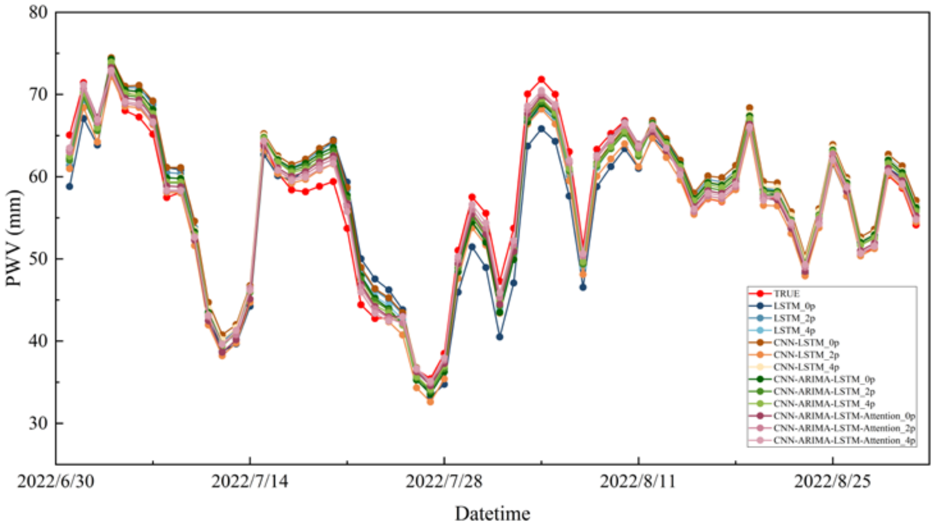
The data collected in the field usually contain a certain amount of noise due to the interference of various random factors, in order to avoid the model fitting noise, it is necessary to carry out noise reduction on the monitoring data, extract the trend term input to the model for prediction, and then the prediction results will be evaluated with the accuracy of the trend term after noise reduction.

In this study, wavelet noise reduction is used to process the monitoring data. The specific noise reduction process is as follows: firstly, different wavelet basis functions and decomposition layers are selected to carry out wavelet decomposition of the target monitoring point data. Secondly, signal-to-noise ratio (SNR) and Root Mean Square Error (RMSE) are calculated respectively, and the wavelet basis functions and decomposition layers are selected according to the higher signal-to-noise ratio and the smaller root-mean-square error. Then the noise reduction threshold is set using the VisuShrink method, and the threshold function uses a hard threshold function; finally, the noise reduction threshold is obtained by wavelet reconstruction. The monitoring data after noise reduction is obtained by wavelet reconstruction. In this study, when the wavelet basis function is db10 and the number of decomposition layers is 3, the signal-to-noise ratio is 18.474 db and the root mean square error is 5.436 mm, which is the best noise reduction effect.

Analysis of Experimental Results

The comparison of the prediction results and the relative error of prediction of the optimized CNN-ARIMA-LSTM-Attention, CNN-LSTM-Attention, CNN-LSTM and LSTM with different numbers of feature inputs of the SMA algorithm are plotted as line graphs as shown in Figures 4 and 5.

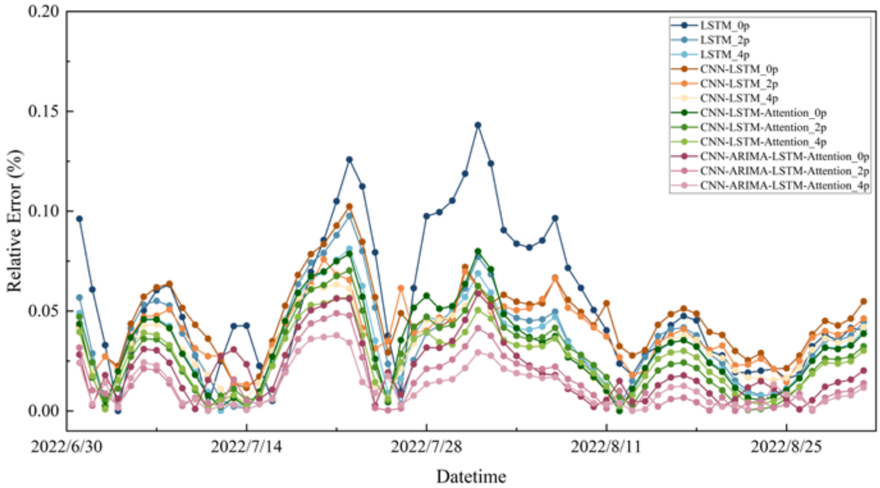
Figure 4. *Plot of PWV Prediction Results for Monitoring Point HKKP*



Comparing the same models with different feature inputs, increasing the number of monitoring points as feature inputs improves the prediction results of all four models. Among them, for CNN-LSTM-Attention, CNN-LSTM and LSTM, the enhancement of model prediction effect by increasing feature input is not significant. For the CNN-ARIMA-LSTM-Attention model, increasing feature inputs significantly improves the prediction effect of the model.

Comparing different models with the same feature input, although the CNN-LSTM-Attention predicts better than the CNN-LSTM, the enhancement is limited, and there is still a certain gap with the observed values after noise reduction. After adding the attention mechanism to the CNN-LSTM-Attention, the prediction effect of the model is significantly improved. At the same time, as the number of prediction periods increases, the CNN-ARIMA-LSTM-Attention is obviously more advantageous, and can better approach the observed values after noise reduction.

Figure 5. *Comparison of the Relative Error of PWV Prediction for HKKP at Monitoring Point*



In order to describe the prediction accuracy of each model more objectively, the results of the evaluation indexes of the four models with different feature inputs are plotted against the accuracy improvement in Tables 2-4. As can be seen in Table 3, the prediction accuracies of the four models are improved by adding feature inputs. Among them, the MAE and RMSE of the CNN-ARIMA-LSTM-Attention model are reduced by 17.58% and 14.25%, respectively, which is remarkable. From Table 4, when the number of feature inputs is 4, the MAE and RMSE of the CNN-LSTM model are reduced by 14.22% and 6.55%, respectively, compared with the LSTM model; the MAE and RMSE of the CNN-LSTM-Attention model are reduced by 4.42% and 2.21%, respectively, compared with the CNN-LSTM model; the MAE and RMSE of the CNN-ARIMA-LSTM-Attention model reduced the MAE and RMSE by 13.29% and 15.85%, respectively, compare to the CNN-ARIMA-LSTM model.

Table 2. *Prediction Accuracy of the Four Models of HKKP at Monitoring Stations*

Number of features	Models	MAE (mm)	MSE (mm)	RMSE (mm)	MAPE	R^2
4p	CNN-ARIMA-LSTM-Attention	1.50	6.02	2.23	0.03	0.96
	CNN-LSTM-Attention	1.73	6.32	2.65	0.04	0.95
	CNN-LSTM	1.81	6.95	2.71	0.04	0.94
	LSTM	2.11	7.96	2.90	0.05	0.93
2p	CNN-ARIMA-LSTM-Attention	1.61	6.52	2.40	0.04	0.95
	CNN-LSTM-Attention	1.89	6.91	2.71	0.04	0.95
	CNN-LSTM	1.98	7.21	2.77	0.04	0.94
	LSTM	2.31	8.85	2.99	0.05	0.93
0p	CNN-ARIMA-LSTM-Attention	1.82	7.02	2.53	0.04	0.94
	CNN-LSTM-Attention	2.15	8.43	2.89	0.05	0.94
	CNN-LSTM	2.26	9.18	3.07	0.05	0.94
	LSTM	3.36	18.09	4.36	0.09	0.90

Notes: MAE is the mean absolute error; MSE is the mean square error; RMSE is the root mean square error; MAPE is the mean absolute percentage error.

Table 3. *Accuracy Improvement after Adding Feature Inputs to Monitoring Station HKKP*

Evaluation indicators	**MAE (%)**		**MSE (%)**		**RMSE (%)**	
Number of features	**2**	**4**	**2**	**4**	**2**	**4**
CNN-ARIMA-LSTM-Attention	11.54	17.58	7.12	14.25	5.14	11.86
CNN-LSTM-Attention	12.09	15.81	18.03	25.03	6.23	8.30
CNN-LSTM	12.39	23.45	21.46	24.29	9.77	11.73
LSTM	31.25	37.20	51.08	56.00	31.42	33.49

Table 4. *Accuracy Improvement of Monitoring Station HKKP with Addition of Different Modules*

	Addition to the ARIMA module	**Addition to the Attention module**	**Addition to the CNN module**
MAE (%)	13.29	4.42	14.22
MSE (%)	4.75	9.06	12.69
RMSE (%)	15.85	2.21	6.55

Discussion

Accurately predicting GNSS PWV is essential for enhancing weather forecasts and understanding atmospheric moisture dynamics. A hybrid model that integrates the SMA, CNN, ARIMA, LSTM, and Attention mechanisms can significantly improve the accuracy of GNSS-PWV predictions. This discussion explores the components and advantages of this sophisticated hybrid model.

(1) SMA algorithm: The SMA is a cutting-edge optimization technique that draws inspiration from slime molds' feeding habits. It efficiently searches for optimal solutions in high-dimensional spaces by mimicking the natural process of slime molds finding food. In the hybrid model, SMA is used to optimize the hyperparameters and weights of the CNN, ARIMA, LSTM, and Attention components. This optimization enhances the overall performance and convergence speed of the model, ensuring that the best possible configuration is used for PWV prediction.

(2) CNN: CNN is adept at extracting spatial features from data. In GNSS-PWV prediction, CNN processes the PWV data to identify significant spatial patterns and relationships. By applying convolutional and pooling layers, CNN transforms raw PWV data into feature maps that capture essential spatial dependencies. These spatial features form a robust basis for the subsequent time series analysis, enabling a more comprehensive understanding of the data's structure.

(3) ARIMA Model: The ARIMA model is a well-established statistical tool for time series analysis. It captures temporal dependencies and trends in PWV data by decomposing the time series into autoregressive and moving average components, with differencing to ensure stationarity. ARIMA effectively filters out noise and highlights underlying temporal patterns, providing a smoothed and

stable input for the LSTM network. This preprocessing step enhances the accuracy and reliability of the subsequent predictions.

(4) LSTM Network: Recurrent neural networks such as LSTM networks are made to deal with long-term dependencies in time series data. They use gates (input, forget, and output) to manage the flow of information, enabling the network to retain and utilize relevant past information over extended periods. In the hybrid model, the LSTM network processes the temporally smoothed data from the ARIMA model, capturing both short-term fluctuations and long-term trends in PWV data. This results in more precise and dependable predictions.

(5) Attention Mechanism: The Attention mechanism enhances the model's ability to focus on crucial time steps by dynamically assigning weights to different inputs. When integrated with LSTM, Attention allows the model to prioritize significant moments in the historical data, improving the prediction of future PWV values. The Attention mechanism computes a weighted sum of past time steps, generating a context vector that emphasizes important temporal patterns, thereby refining the prediction process.

Integrating SMA, CNN, ARIMA, LSTM, and Attention mechanisms leverages the strengths of each component:

(1) Enhanced Accuracy: The hybrid model provides a comprehensive understanding of PWV data by incorporating both spatial and temporal features, leading to more accurate predictions than single models.
(2) Effective Noise Reduction: The combination of ARIMA and LSTM smooths the data and captures complex temporal dependencies, minimizing the impact of noise on predictions.
(3) Optimized Performance: The use of SMA for hyperparameter and weight optimization ensures the model operates at its best possible configuration, enhancing predictive accuracy and efficiency.
(4) Adaptive Focus: The Attention mechanism allows the model to dynamically adjust its focus on relevant historical data, improving its responsiveness to changing trends.

This hybrid model holds significant promise for meteorological applications, particularly in predicting GNSS-PWV and improving rainfall forecasts. By integrating advanced optimization techniques, deep learning, and traditional statistical methods, the hybrid model offers a powerful tool for weather prediction, aiding in better disaster preparedness and resource management. Further research and refinement of this model could lead to even greater improvements in prediction accuracy and practical applications in meteorology and climate science.

Conclusions

In this study, based on the existing CNN-LSTM, the attention mechanism and ARIMA module are added to propose a combined CNN-ARIMA-LSTM-Attention model that can extract the key information of the monitoring data, and at the same time increase the number of neighboring monitoring points as feature inputs, which is applied to the GNSS water vapor prediction, and the following conclusions are drawn:

(1) While adding more features to a model might increase its prediction accuracy, the accuracy gain varies depending on the model. The experimental results show that the combination models with more complex structure such as CNN-ARIMA-LSTM-Attention and CNN-LSTM-Attention can effectively extract the spatial features of multiple monitoring points, and the average accuracy enhancement is over 30% after adding feature inputs. The relatively simple CNN-LSTM and LSTM models are difficult to effectively extract the spatial features of multiple monitoring points in a multi-feature input dataset, and the accuracy improvement is below 30%.

(2) Adding CNN modules can significantly improve the prediction accuracy of the models. The experimental results show that the accuracy improvement of CNN-LSTM is more than 10%. This indicates that CNN can extract the spatial features of target monitoring points and neighboring monitoring points, which can make the LSTM network easier to capture the dependence of multi-dimensional feature time series, and can achieve better prediction results compared to the single-model LSTM network.

(3) The accuracy of the predictions can be greatly increased by including the attention mechanism. The experimental findings demonstrate that the addition of the attention mechanism improves the accuracy of the CNN-LSTM-Attention and CNN-ARIMA-LSTM-Attention combination models by more than 2%. This suggests that the attention mechanism is capable of successfully directing the neural network's attention to the important details in the multidimensional feature time series data, preventing overfitting in the model's training phase, and enabling higher prediction accuracy in the test set.

(4) Adding ARIMA module can significantly improve the prediction accuracy. The experimental results show that the accuracy of the CNN-ARIMA-LSTM- Attention after adding the ARIMA model is improved by more than 13%. This indicates that the ARIMA is able to effectively deal with the data of non-stationary time series and reveal the inherent structure and laws in them, so as to make accurate predictions.

In summary, the CNN-ARIMA-LSTM-Attention time series prediction neural network optimized by the SMA algorithm proposed in this paper not only solves the problem of neural network's difficulty in focusing on the key information in multidimensional feature time series data in order to improve the model's generalization ability, but also solves the problem of not being able to adaptively obtain the locally optimal hyper-parameter combinations under the conditions of different experimental data and different experimental models. In addition, it is also investigated that increasing the number of neighboring monitoring points as feature inputs can improve the model accuracy. Therefore, compared with the existing water vapor prediction models, the CNN-ARIMA-LSTM-Attention combined model has a complete architecture, with the functions of feature extraction, feature screening, time-series prediction, and hyperparameter optimization, and has strong adaptive and generalization abilities, which can be applied to high-precision water vapor prediction, and provide references and guides to weather forecasting and climate monitoring.

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A General Model for Representing Knowledge - Intelligent Systems Using Concepts

By Thomas Fehlmann[*] & Eberhard Kranich[±]

Arrow terms of the form $\{a_1, a_2, \ldots, a_n\} \to b$ have been proposed by Scott and Engeler, 50 years ago, as a model for combinatory logic. Since combinatory logic is Turing-complete, the model causes interest for domains dealing with knowledge, such as artificial intelligence. It has been used to model neural networks – how does the brain think – and connect the notion of computability with observability in natural science. In software testing, arrow terms serve as representation for test cases that allow combination, and thus automated generation of more test cases for testing complex systems. However, knowledge is not a well-defined notion. It is sometimes referred to as awareness of facts or as practical skills and may also refer to familiarity with objects or situations. Knowledge of facts is distinct from opinion or guesswork by virtue of justification. Facts are usually described as a set of conditions, followed by a consequence. This makes the arrow term model an accurate model for knowledge. Knowledge about facts can lead to theories. A theory is knowledge under control. Theories can be approximated by control sequences. The combination of knowledge and theories makes up for intelligent systems.

Keywords: *combinatory logic, arrow term models, artificial intelligence, learning systems, intelligent systems, intuitionism*

Introduction

Paper Intent

In the early 20th century, there were some shocking events taking place in mathematical logic and natural science. Gödel (1931), when trying to solve some of Hilbert's 23 problems, detected that predicate logic, something with a very long history dating back to the ancient Greeks, see Engeler (2020), is undecidable. This insight gave birth to theoretical computer science, including the theory of computation, founded by Turing (1937). For a modern compilation, see e.g., Raatikainen (2020).

Schönfinkel and Curry developed *Combinatory Logic* (Curry & Feys 1958) to avoid the problems introduced when using logical quantifiers, and Church invented *Lambda Calculus* as a rival formalism (Church 1941). Scott and Engeler developed the *Graph Model* (Engeler 1981), based on *Arrow Terms*, and proved that this is a model of combinatory logic. This means that you can combine sets of arrow terms to get new arrow terms, and that combinators, accelerators, and constructors can be used to create new elements of algebra.

[*]Senior Research, Euro Project Office AG, Switzerland.
[±]Senior Research, Euro Project Office AG, Switzerland.

Graphs in the form of neural networks appeared already at the origins of *Artificial Intelligence* (AI). Its first instantiation in modern times was the *Perceptron*, a network of neurons postulated by Rosenblatt (Rosenblatt 1957). It later became a directed graph (Minsky & Papert 1972). Rosenblatt was also the first postulating concepts, among perception and recognition, as constituent parts of AI (Rosenblatt 1957, p. 1).

Since its origins, AI has experienced difficulties; however, today it seems to have become mainstream as far as there are many AI applications that provide value for the user. In some areas, training an AI model is much simpler and more rewarding than finding and programming an algorithm (Nico Klingler (viso.ai) 2024).

Nevertheless, temporal patterns (Rosenblatt 1957, p. 2) still are not available in AI and provide quite a challenge, as exemplified by the ARC challenge, a sort of intelligence test for AI models, proposed by Chollet (2019).

The Graph Algebra of Arrow Terms

Let $\mathcal{L}$ be a non-empty set. Engeler (1981) defined a *Graph* as the set of ordered pairs:

$$\langle \{b_1, b_2, \dots, b_m\}, c \rangle \tag{1}$$

with $b_1, b_2, \dots, b_m, c \in \mathcal{L}$. We prefer to write $\{a_1, \dots, a_m\} \to b$ instead of the ordered pair to make notation mnemonic and call them *Arrow Terms*. These terms describe the constituent elements of directed graphs with multiple origins and a single node. We extend the definition of arrow terms to include all formal set-theoretic objects recursively defined as follows:

$$\begin{gathered} \text{Every element of } \mathcal{L} \text{ is an arrow term.} \\ \text{Let } a_1, \dots, a_m, b \text{ be arrow terms.} \\ \text{Then } \{a_1, \dots, a_m\} \to b \text{ is also an arrow term.} \end{gathered} \tag{2}$$

The left-hand side of an arrow term is a finite set of arrow terms, and the right-hand side is a single arrow term. This definition is recursive. Elements of $\mathcal{L}$ are also arrow terms. The arrow, where present, should suggest the ordering in a graph, not logical imply.

The Algebra of Observations

Let now $\mathcal{L}$ be more specific, namely the non-empty set of assertions over certain objects of the real world, observable and recognizable by suitable AI models, in some formal language about that domain. Examples include statements about gravity, temperature, matter, molecules, or any object that can be tagged using AI (Nico Klingler (viso.ai) 2024).

Denote by $\mathcal{G}(\mathcal{L})$ the power set containing all arrow terms of the form (2). The formal definition in set-theoretical language is given in equation (3) and (4):

$$\mathcal{G}_0(\mathcal{L}) = \mathcal{L}$$
$$\mathcal{G}_{n+1}(\mathcal{L}) = \mathcal{G}_n(\mathcal{L}) \cup \{\{a_1, \dots, a_m\} \to b | a_1, \dots, a_m, b \in G_n(L), m \in \mathbb{N}\} \quad (3)$$
$$\text{for } n = 0, 1, 2, \dots$$

The definition is recursive. Thus, $\mathcal{G}(\mathcal{L})$ is the set of all (finite and infinite) subsets of the union of all $\mathcal{G}_n(\mathcal{L})$:

$$\mathcal{G}(\mathcal{L}) = \bigcup_{n \in \mathbb{N}} \mathcal{G}_n(\mathcal{L}) \quad (4)$$

The elements of $\mathcal{G}_n(\mathcal{L})$ are arrow terms of level n. Terms of level 0 are named *Observations*, a finite set of arrow terms of level 1 or higher is called *Concept*; finite or infinite sets of arrow terms, including observations and concepts, are called *Knowledge*.

The definition of an application between two finite or infinite sets of arrow terms M, N – observations, concepts, and knowledge equally – makes $\mathcal{G}(\mathcal{L})$ an algebra:

$$M \bullet N = \{c | \exists \{b_1, b_2, \dots, b_m\} \to c \in M;\ b_i \in N\} \quad (5)$$

$\mathcal{G}(\mathcal{L})$ is closed under the application operation.

According to Engeler (Engeler, 1981), the motivation behind this definition is, when starting with observations about some domain, arrow terms represent knowledge about that domain. Examples include the *Neural Algebra* of Engeler (2019). Thus, it might be of interest to engineers who want to handle knowledge, and in fact, AI was the ultimate vision at the time the graph model was conceived (Engeler 1995).

Why the Left Hand of a Concept Must be a Set, Not a Conjunction

The use of a set for the left-hand side of an element of a concept is essential; if one tries with a conjunction, one gets a model for typed lambda calculus, see Bimbó (2012). Such models may still have interesting properties; in some respect, they produce deterministic outcomes and are easy to prove for correctness; however, they are not relevant for AI.

Today's world of intelligent and smart products is far from producing deterministic outcomes, and some products have cyber-physical effects on their environment that might harm people; thus, are safety relevant. Examples include autonomous vehicles and medical instruments but are today growing rapidly.

The difference between conjunctions and sets is that sets might contain contradictory elements, annihilated by conjunctions. For software testing, especially for testing smart systems using AI und *Deep Learning*, it is of essence. In the famous case of the Tempe crash (March 18, 2018), the crash report shows that the scenario recognition system of the autonomous car on its supervised trial run had seven seconds to react – sufficient for an emergency break – but recognized three different objects: a person, a bike, and plastic bags. These perceptions are mutually excluding, but you would never allow an autonomous car emergency breaking because of a plastic bag, but exactly such different perceptions happen in the real world. Intelligent things as well as humans experience this. A test bench must therefore never require test data to be consistent if it's required to test safety relevant features, such as whether an autonomous car starts the risky action of an emergency stop.

Intelligent Systems

There is currently a lot of talk about AI, including *Large Language Models* (LLM), which have the potential to change the way we work. AI systems have a stunning ability to collect information, learn from them, and deliver responses to related questions, without programming (Wolfram 2023). However, how do observations connect to the real world? Referring to objects that exhibit some usual behavior?

This process is called *Grounding* (Zhong, et al. 2022). Every human knows that gravity prevents heavy objects from flying, something that is easily expressed by a concept, but today's AI can just collect observations about heavy objects and derive a model out of this. Quite a tedious process. It needs a huge bunch of samples until it "knows" about the effect of gravity. By grounding an observation to a known object of the real world, the intelligent system should know.

The kind of knowledge that allows grounding, and much more, are *Concepts*. We will show how to implement concepts in Engeler neural algebra.

Research Questions

In this paper, we discuss several open points:

1. What is a suitable theoretical foundation of AI?
2. Does handling knowledge with concepts enable intelligent systems (AI) to learn faster and become more predictable?
3. How should intelligent systems evolve to incorporate the arrow term algebra into their behavior?
4. Will intelligent systems ever be able to solve unfamiliar problems on their own?

Paper Content

We start with an introduction to Combinatory Logic and explain why this logical construct is of interest both to mathematicians who are looking at the foundations of their science, as well as to engineers who want to build intelligent products.

Next, we introduce Arrow Terms as a model for combinatory logic and explain what it has to do with intuitionism. We explain why arrow terms serve as a generalization of knowledge and how concepts might be used to solve problems.

Then we explore the possibility of programming concepts. The intelligent system might combine such concepts, to the possibility of creating new concepts out of combining them, based on observations by the machine itself.

Finally, we outline a few conclusions and answer the research question.

Combinatory Logic

Combinatory Logic and the Axiom of Choice

Combinatory Logic is a notation to eliminate the need for quantified variables in mathematical logic, and thus the need to explain what means $\exists x \in M$, "there exists some x in some set M", see Curry and Feys (1958) and Curry et al. (1972). Eliminating quantifiers is an elegant way to avoid the *Axiom of Choice* (Fehlmann & Kranich 2020) in its traditional form. Combinatory Logic can be used as a theoretical model for computation and as design for functional languages (Engeler, 1995); however, the original motivation for combinatory logic was to better understand the role of quantifiers in mathematical logic.

It is based on *Combinators* which were introduced by Schönfinkel in 1920. A combinator is a higher-order function that uses only functional application, and earlier defined combinators, to define a result from its arguments.

The combination operation is denoted as $M \bullet N$ for all combinatory terms M, N. To make sure there are at least two combinatory terms, we postulate the existence of two special combinators $\mathbf{S}$ and $\mathbf{K}$. They are characterized by the following two properties (6) and (7):

$$\mathbf{K} \bullet P \bullet Q = P \tag{6}$$
$$\mathbf{S} \bullet P \bullet Q \bullet R = P \bullet Q \bullet (P \bullet R) \tag{7}$$

where P, Q, R are terms in combinatory logic[1]. The combinator $\mathbf{K}$ acts as projection, and $\mathbf{S}$ is a substitution operator for combinatory terms. Equations (6) and (7) act like axioms in traditional mathematical logic.

[1]The use of variables named P, Q, R is borrowed from Engeler (2020).

Like an assembly language for computers, or a Turing machine, the $\mathbf{S}$-$\mathbf{K}$ terms become quite lengthy and are barely readable by humans, but they work fine as a foundation for computer science.

The power of these two operators is best understood when we use them to define other, handier, and more understandable combinators: The identity combinator for instance is defined as

$$\mathbf{I} \coloneqq \mathbf{S} \bullet \mathbf{K} \bullet \mathbf{K} \tag{8}$$

Indeed, $\mathbf{I} \bullet M = \mathbf{S} \bullet \mathbf{K} \bullet \mathbf{K} \bullet M = \mathbf{K} \bullet M \bullet (\mathbf{K} \bullet M) = M$. Association is to the left.

Moreover, $\mathbf{S}$ and $\mathbf{K}$ are sufficient to build a Turing-machine. Thus, combinatory logic is Turing-complete. For a modern proof, consult Barendregt (Barendregt & Barendsen 2000, pp. 17-22).

Functionality by the Lambda Combinator

Curry's *Lambda Calculus* (Barendregt 1977) is a formal language that can be understood as a prototype programming language. The $\mathbf{S}$-$\mathbf{K}$ terms implement the lambda calculus by recursively defining the *Lambda Combinator* $\mathbf{L_x}$ for a variable x as follows:

$$\begin{aligned} &\mathbf{L_x} \bullet x = \mathbf{I} \\ &\mathbf{L_x} \bullet Y = \mathbf{K} \bullet Y \text{ if } Y \text{ different from } \mathbf{x} \\ &\mathbf{L_x} \bullet M \bullet N = \mathbf{S} \bullet \mathbf{L_x} \bullet M \bullet \mathbf{L_x} \bullet N \end{aligned} \tag{9}$$

The definition holds for any term $\mathbf{x}$ of combinatory logic. Usually, on writes suggestively $\lambda x.M$ instead of $\mathbf{L_x} \bullet M$, for any combinatory term M. Note that $\lambda x.M$ is a combinatory term, as proofed by (9), and that we now introduced some sort of variable into combinatory logic with a precise binding behavior.

The Lambda combinator allows writing programs in combinatory logic using a higher-level language. When a Lambda term gets compiled, the resulting combinatory term is like machine code for traditional programming languages.

The Fixpoint Combinator

Given any combinatory term Z, the *Fixpoint Combinator* $\mathbf{Y}$ generates a combinatory term $\mathbf{Y} \bullet Z$, called *Fixpoint of* Z, that fulfills $\mathbf{Y} \bullet Z = Z \bullet (\mathbf{Y} \bullet Z)$. This means that Z can be applied to its fixpoint as many times as wanted and still yields back the same combinatory term.

In linear algebra, such fixpoint combinators yield an eigenvector solution to some problem Z; for instance, when solving a matrix in linear algebra (Fehlmann 2016). It is therefore tempting to say, that $\mathbf{Y} \bullet Z$ is a solution for the problem Z.

According to Barendregt and Barendsen (2000, p. 12), the fixpoint combinator can be written as

$$\mathbf{Y} := \lambda f.\big(\lambda x.f \bullet (x \bullet x)\big) \bullet \big(\lambda x.f \bullet (x \bullet x)\big) \tag{10}$$

Translating (10) into an **S**-**K** term proves possible but becomes a bit lengthy. It demonstrates how combinatory logic works; consult Fehlmann & Kranich (2022). For more sample combinators, consult Zachos (1978).

However, the fixpoint combinator is not the solution to all our problems. When applying **Y**, or any other equivalent fixpoint combinator to a combinatory term *Z*, reducing the term by repeatedly using rule (6) and (7) does not always terminate. An infinite loop can occur, and must sometimes occur, otherwise Turing would be wrong and all finite state machines would reach a finishing state (Turing 1937).

The Graph Model of Combinatory Logic

Why a Model?

A *Model* for a logical structure is a set-theoretic construction that has the properties postulated for the logic and can be proved to be non-empty. Then it means that logic makes sense as far as it describes some structure that really exists.

Einstein-Notation for Arrow Terms

To avoid the many set-theoretical parenthesis, the following notation, called *Arrow Schemes*, is applied, in analogy to the Einstein notation (Fehlmann 2020, p. 6):

a_i for a finite set of arrow terms, i denoting some *Choice Function* selecting finitely many specific terms out of a set of arrow terms a.
a_1 for a singleton set of arrow terms; i.e., $a_1 = \{a\}$ where a is an arrow term. (11)
$\emptyset$ for the empty set, such as in the arrow term $\emptyset \to a$.
$a_i + b_j$ for the union of two sets a_i and b_j of observations.

The application rule for M and N now reads:

$$M \bullet N = (b_i \to a) \bullet N = \{a | \exists b_i \to a \in M;\ b_i \subset N\} \tag{12}$$

where $(b_i \to a) \subset M$ is the subset of level 1 arrow terms in M. With these conventions, $(x_i \to y)_j$ denotes a *Concept*, i.e., a non-empty finite set of arrow terms with level 1 or higher, together with two choice functions i, j. Each set element has at least one arrow.

The choice function chooses some specific observations a_i out of a (larger) set of observations a. This is what Zhong describes as *grounding* when linking observations to real-world objects (Zhong et al. 2022). If a denotes knowledge, i.e., an infinite set of arrow terms of any level, a_i can become part of a concept consisting of specific arrow terms referring to some specific sample knowledge, specified by the choice function j. Choice functions therefore have the power of focusing knowledge on specific objects in specific areas. That makes choice functions interesting for intelligent systems and AI.

There is a conjunction of choice functions, thus $a_{i,j}$ denotes the union of a finite number of m concepts:

$$a_{i,j} = a_{i,1} \cup a_{i,2} \cup \ldots \cup a_{i,j} \cup \ldots \cup a_{i,m} = \bigcup_{k=1}^{m} a_{i,k} \tag{13}$$

There is also cascading of choice functions. Let $N = \left(a_j \to x\right)_k$ then:

$$\begin{gathered} M = \left(\left(\left(a_j \to x\right)_k \to x_i\right)_l \to y\right) \text{ and} \\ M \bullet N = \left(x_{i_l} \to y\right) \end{gathered} \tag{14}$$

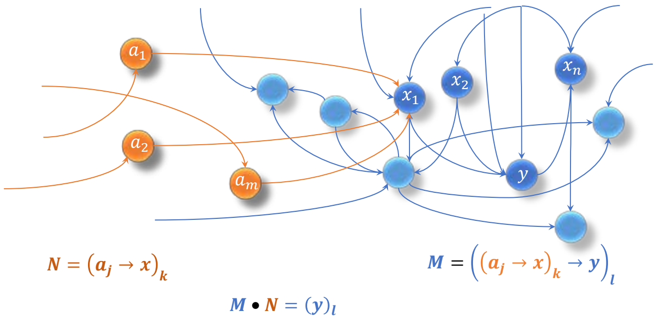
The choice function might be used for grounding a concept to observations.

An arrow scheme without outer indices represents a potentially infinite set of arrow terms. Thus, writing a, we mean knowledge about an observed object. Adding an index, a_j, indicates such a grounded object together with a choice function j that chooses finitely many specific observations or knowledge.

While on the first glimpse, the Einstein notation seems just another way of denoting arrow terms, for representing such data in computers it means that the simple enumeration of finite data sets is replaced by an intelligent choice function providing grounding that must be computed and can be either programmed or guessed by an intelligent system.

Interestingly, as the name “graph model” suggests, arrow terms are just an algebraic way of describing neural networks. Thus, something that nature uses to acquire and work with knowledge.

Figure 1. *A Neural Network as a Combinatorial Algebra*



Combination according to equation (12) yields what we perceive as "response from a neural network." Thus, combinators play a significant role in AI.

The Graph Model – A Model of Combinatory Logic

The algebra of observations represented as arrow terms is a combinatory algebra and thus a model of combinatory logic. The following definitions demonstrate how observations implement the combinators $\mathbf{S}$ and $\mathbf{K}$ fulfilling equations (6) and (7).

$$
\begin{aligned}
&\mathbf{I} = a_1 \to a \text{ is the Identification, i.e., } (a_1 \to a) \bullet b = b \\
&\mathbf{K} = a_1 \to \emptyset \to a \text{ selects the 1}^{\text{st}} \text{ argument:} \\
&\quad \mathbf{K} \bullet\ b \bullet \mathrm{c} = (b_1 \to \emptyset \to b) \bullet b \bullet \mathrm{c} = (\emptyset \to b) \bullet \mathrm{c} = \mathrm{b} \\
&\mathbf{KI} = \emptyset \to a_1 \to a \text{ selects the 2}^{\text{nd}} \text{ argument:} \\
&\quad \mathbf{KI}\ \bullet b \bullet \mathrm{c} = (\emptyset \to c_1 \to c) \bullet b \bullet \mathrm{c} = (c_1 \to c) \bullet c = \mathrm{c} \\
&\mathbf{S} = \left(a_i \to \left(b_j \to c\right)\right)_1 \to (d_k \to b)_i \to \left(a_i + b_{j,i} \to c\right)
\end{aligned}
\tag{15}
$$

Therefore, the algebra of observations is a model of combinatory logic. The interested reader can find complete proofs in Engeler (Engeler 1981, p. 389).

With $\mathbf{S}$ and $\mathbf{K}$, an abstraction operator can be constructed that builds new knowledge bases, following equation (9) (9). In the setting of a combinatory algebra, this is called *Lambda Theorem*; see Barendregt (Barendregt 1977).

Instances of the Graph Model

Number Theory

The assertions $\mathcal{L}$ might be numerical formulas. Then $\mathcal{G}(\mathcal{L})$ is the knowledge about number theory that can be combined and processed using the lambda calculus, or solved by fixpoint combinators, or controlled by some controlling combinators. The latter is better known as infinite series, with or without convergence.

Graph Theory

Obviously, the graph model takes its name from directed graphs, where each arrow term represents a node with its predecessors. Neural networks have such a structure. With the graph model, neural networks become properties of an algebra, see equations (6) and (7). For AI, this is interesting because it explains how to implement concepts.

Quality Function Deployment (QFD)

QFD can also be represented by the graph model; the arrow terms become then Ishikawa-diagrams. Sets of arrow terms, or Ishikawa-diagrams, can be represented by matrices. They were indeed at the roots of QFD (Fehlmann 2016, p. 321). QFD is less versatile than AI because the matrices have limited size and learning is by capturing experts' knowledge, not training by big data, but otherwise there are many similarities between QFD and AI.

Neural Network

Engeler used the arrow term model to explain how the brain thinks. The Graph Model of Combinatory Logic explains how complex scripts of behavior and conceptual content can reside in, combine, and interact on large neural networks. The neural hypothesis attributes functions of the brain to sets of firing neurons dynamically: to cascades of such firings, typically visualized by imaging technologies.

Such sets are represented as the elements of what Engeler calls a *Neural Algebra* with their interaction as its basic operation. The neuro-algebraic thesis identifies "thoughts" with elements of a neural algebra and "thinking" with its basic operation (Engeler 2019).

Engeler argues for this thesis by a thought-experiment. It examines examples of human thought processes in proposed emulation by neural algebras. Problems such as controlling, classifying, and learning are analyzed. In neural algebras these may be posed as algebraic equations, whose solutions may lead to extensions of a neural algebra by new elements. Modelling of such extensions consists of formal analogues to familiar faculties such as reflection, distinction and comprehension which can be made precise as operations on the algebra. Barendregt gives handy examples of such precise algebra operations in the chapter about "The Power of Lambda Calculus" in his seminal book (Barendregt 1984, pp. 17-22).

An advantage of such an approach is that this modelling leads directly to brain functions. From the cascades of such functions, we obtain the neurons involved in them, and their connective structure, and can mathematically describe their behavior using the graph model.

Autonomous Real-time Testing

Fehlmann (2020) proposes the arrow term model for automatically creating test cases for complex systems. Instead of observations, the domain $\mathcal{L}$ consists of assertions about the status of the program under test, and the level 1 arrow terms describe test cases. Sets of test cases can be combined as any arrow term sets and allow developing new test cases automatically.

Controlling operators, see next section, are usually quite simple: in most cases, it is sufficient to combine test cases on the lowest possible level, i.e., on $\mathcal{G}_1(\mathcal{L})$, and connect them with their value for the user. This is especially useful when testing large, complex systems of systems ensuring correct cooperation between different component systems.

Higher-level controlling operators are conceivable and might become of essence for testing intelligent systems. Testing concepts, if reused, have the potential to become the most important asset of companies providing intelligent products.

Controlling Combinators

The Need for a Temporal Extension in AI

AI-powered Visual Recognition Systems excel in recognizing and classifying objects. However, they are weak at recognizing temporal dependencies and unable to combine learnings. AI lacks what humans use in such cases: a concept.

Controlling Combinators for Solving the Control Problem

The concept of *Control* involves a *Controlling Operator* $\mathbf{C}$ which acts on a controlled object X by application $\mathbf{C} \bullet X$. Control means that the knowledge represented by X is completely known and described. It is a similar approach to establishing a fixpoint.

Accomplishing control can be formulated by:

$$\mathbf{C} \bullet X = X \tag{16}$$

The equation (16) is a theoretical statement, usually an infinite loop process.

For solving practical problems, X must be approximated by finite subterms.

The control problem is solved by a *Control Sequence* $X_0 \subseteq X_1 \subseteq X_2 \subseteq \cdots$, a series of finite subterms, determined by (17):

$$X_{i+1} = \mathbf{C} \bullet X_i, i \in \mathbb{N} \tag{17}$$

starting with an initial X_0. This is called *Focusing*. The details can be found in Engeler (2019, p. 299). The controlling operator $\mathbf{C}$ gathers all faculties that may help in the solution. Like equation (10), controlling operators consist of structural content than of single observations. The control problem is a repeated process of substitution, like finding the fixpoint of a combinator.

Within this setting, it is possible to define models for reasoning (Engeler 2019), problem solving, and software and systems testing (Fehlmann & Kranich 2019).

Use the Choice Function for Grounding

A *Concept of Level 1* consists of a set of arrow terms of the form (18)

$$x_j \to y \tag{18}$$

where x denotes observations. The choice function j selects specific observations for some real-world object. With Zhong et al. (2022), we use the term “grounding” for such choice functions. The response y describes the expected properties of the observations x. The choice function j appears again in y, specifying expected behavior or properties that are consequences from the observations x_j. With such a concept, we can describe behavior of real-world objects that are otherwise hard for an intelligent system to guess.

The choice function j is computable and constructive, referring to the properties of the base elements of the set of observations x. According to the Lambda theorem (9), it can be programmed. The concept based on choice functions grounds arrow schemes to basic observations.

The knowledge acquired by new observations growths:

$$X_0 \subseteq X_1 \subseteq X_2 \subseteq \cdots \tag{19}$$

Thus, the index creates a control sequence (19), formally in the same way as Engeler explains how the brain thinks (Engeler 2019, p. 301).

Programming the Choice Function

The more concepts an intelligent system has at its disposal, the faster it will solve problems, and the more reliable and predictable will its decisions be. It is therefore a clever idea to write domain-specific concepts beforehand. Neither for humans nor for intelligent systems, training the choice function is a simple task. However, because we use combinatory algebra, concepts can be combined. For instance, we might combine a concept looking for pixels with a specific color logo with another exploring specific positioning between the pixels of interest.

Concepts thus seem an approach to add a sort of external programmability to intelligent machines that blast the existing paradigm of "Learning" in AI. We no longer are restricted to training neural networks and creating models – in fact, by multilinear optimization – but add the capabilities of modern algorithmic programming. The arrow terms "assembly language" is the layer where combination occurs. On this layer, concepts can combine with observations and increase knowledge. Higher level concepts might add new power to concepts. Thus, this serves as a strong motivation to continue with the explanation of what a "concept" means in the context of the graph model.

Focusing Using Attractors

The control problem is a repeated process of substitution, like finding the fixpoint of a combinator. Within this setting, it is possible to define models for reasoning, problem solving, and scientific observations. However, not only flat reasoning, but also for solving problems, even if their fixpoint is infinite.

Let X be an expandable, unorganized set of observations. Apply the controlling combinator $\mathbf{C}$ to X with the aim to accomplish control, see equation (16). Then, solutions are obtained by *Focusing*:

$$X_{i+1} = \mathbf{C} \bullet X_i,\ i \in \mathbb{N} \tag{20}$$

Starting with initial evidence X_0, the controlling combinator $\mathbf{C}$ creates the control sequence $X_0 \subseteq X_1 \subseteq X_2 \subseteq \cdots$ towards an optimum solution containing all elements of the control sequence, eventually reaching X. This optimum solution is called an *Attractor*. The details can be found in Engeler (2019, p. 301).

In natural science, it is tempting to call such a controlling combinator a *Theory*, since the control sequence predicts evidence.

The concept $\mathbf{C}$ gathers all faculties that may help in finding the solution of a problem. Using the Lambda theorem as of equation (9), concepts consist of structural content than of single observations. The control problem is a repeated process of substitution, like finding the fixpoint of a combinator. Nevertheless, concepts may relate to the domain $\mathcal{L}$ by choice functions $\boldsymbol{j}$. Thus, it is possible to write concepts that meet safety or security requirements. Or, concepts can be used to implement morally aware behavior, for instance avoiding racial or gender bias, even if the AI training set was not perfect. Concepts thus can address societal reservations about AI by controlling grounding references made in the knowledge used for decisions. Concepts can make AI decisions transparent to humans.

Examples of concepts include combinators that extract only a part of knowledge, like $\boldsymbol{K}$ and $\boldsymbol{KI}$, or conditional branching, or conjunction and disjunction. Some concepts repeat actions until a certain condition holds and may repeat actions potentially forever. A concept implements mechanisms known from programming but with references to the grounded objects.

Obviously, it is much easier to create such a conceptually defined controlling combinator by programming techniques, programming the choice function j using the Lambda Theorem (9). Programmers can create controlling combinators that select the objects with suitable properties and give these to the machine as concepts. The intelligent system alone would encounter major difficulties to guess the right indexing choice functions, without help by a programmer.

A Classification of Concepts ("Controlling Combinators")

Concepts exist on various levels:

Indexing Controls describe concepts C that apply the same choice function to different but similar knowledge. Such concepts allow grounding objects of the real world to observations and make learning for intelligent systems much faster. Indexing Controls can be programmed easily and used to teach an intelligent system what gravity is, or how children behave when playing with a football. Such knowledge is easily programmable by choice functions.

Most indexing control concepts remain on level 1 and are easy to handle because humans still can understand what concepts do.

Holding Controls are concepts $\mathbf{C}$ that stop adding more knowledge at a certain point after n steps:

$$X_0 \subseteq X_1 \subseteq X_2 \subseteq \ldots \subseteq X_{\mathrm{n}} = X_{\mathrm{n}+1} = \ldots \text{ for } X_{i+1} = \mathbf{C} \bullet X_i \quad \text{where } X_0 \subseteq X_1 \subseteq X_2 \subseteq \ldots \text{is a control sequence} \tag{21}$$

An example is a finite list of facts $\mathbf{C} \bullet X = X$. Because of the hold at a certain point in time, this is still understandable by humans, and they can follow its reasoning.

***Attractor Control*s** are concepts C that continuously add more knowledge, without limit. An example is the famous fixpoint $\boldsymbol{Y} \bullet Z$ that yields $\mathbf{Y} \bullet Z = Z \bullet (\mathbf{Y} \bullet Z)$ for any given combinator Z.

This is a difficult approach because attractor concepts conceive a higher kind of intelligence than humans usually can exhibit. Human controlling sequences are limited anyway because of the finite lifespan of humans, see Engeler's sample "Neural Model-Mathematician" (Engeler 2019, p. 306). Attractor control concepts are relentlessly adding knowledge from a theory. This iterates that as long as needed, until a stage of knowledge is reached that meets certain predefined quality criteria.

The Problem with Concepts

While the theory looks appalling and easy, and programming in Lambda calculus familiar, transforming a Lambda term into a combinator is tedious, and into a set of arrow terms is something only a machine can do flawlessly. That might be exactly the reason combination of concepts hasn't been studied earlier. Combining arrow term sets simply becomes too complicated. But engineers are frightened by the prospect of computational complexity, as long as it remains controlled.

While programming concepts in Lambda calculus seems not more complicated than writing symbolic programs in Lisp or Scala, transforming Lambda terms into S-K terms, and even more into sets of arrow terms, is far from intuitive and requires help by machines ("Rewrite rules").

Moreover, we can combine concepts not only by functional application ("Currying"), but also by help of higher-level programming concepts such as disjunction, conjunction, or conditional branching, as well as unconditional loops ("For-loops") or even conditional loops that potentially never stop iterations. All these programming concepts can be expressed in combinatory logic and thus might become instrumental for combining concepts for AI systems.

A Roadmap towards Introducing Concepts in Artificial Intelligence

We summarize the arguments given as follows: we have observations made by AI and we use concepts to teach the intelligent system what to do with those observations. It is true that such concepts can be acquired by AI without human help, but this is a tedious and lengthy task. It is easier for a machine to choose concepts from a collection of already existing concepts – which might prove to be successful – than to being trained in them every time from scratch. An initial set of concepts is what human programmers can furnish to an intelligent machine. However, a system can only then be called "intelligent" if it can combine concepts without help from a human.

Joining Forces: Traditional Functional Programming Supports Concepts

Machines learn to recognize and correctly identify objects, both logically and visually, using traditional AI methods, modeling the real world by multilinear optimization. But only concepts enable them to create new problem solutions.

Concepts can be programmed using the DevOps paradigm. An intelligent system needs a minimum selection of concepts to solve real-world problems. In turn, an intelligent system can combine various concepts and select the most promising ones based on *Cost Functions* that reflect relevance for the user.

This is analogue to the invention of flying machines that initially were thought to imitate bird's light, until aerodynamic uplift was better understood. By training traditional models AI will not be able to develop controlling combinators, or concepts, adopting the way brains recognize patterns. Engeler calls for a "Teaching Combinator" that is needed to help brains to develop such concepts. It looks like Panigrahi et.al. have detected a similar capability of large neural networks that they call "Skills" in exceptionally large LLM (Panigrahi et al., 2023).

Using traditional programming enables machines to learn concepts. Programming concepts is possible thanks to Barendregt's Lambda theorem (9). This does not mean that machines cannot become creative and learn to combine concepts themselves - much like humans do. Concepts are elements of combinatory algebra, always allowing for combination. The reader should note once more how important it is to use type-free programming.

The problem with combining concepts is the same as with any deep learning approach: a cost function must be found that allows to choose valuable combinations out of the variety of combinations of concepts. Machines are good at simulation, better than humans. It should not be difficult to define such cost functions based on simulation of event outcomes.

From Creating Concepts to Empathetic, Intelligent Systems

Concepts add dynamic, algorithmic, and temporal intelligence to deep learning, that in turn is static, statistical learning. Programmers tell robots what to do with their static insights, using concepts. In turn, robots can select concepts themselves if found useful. This is a new hybrid humanoid: Deep learning plus algorithms combined.

In a competitive environment, good concepts will become decisive for deciding what intelligent system to acquire, and thus deciding about commercial success or failure of intelligent systems.

Conclusions

Intuitionism and Choice Functions

The Graph Model is an extremely rich structure for representing quite different topics such as

How does the brain think.
Product improvement with focus on customer needs by QFD.
Testing of complex, software-intense systems with thousands of Embedded Control Units (ECU).
Making AI intelligent.

Choice functions offer a constructive way to ground knowledge; existence of a choice always means existence of an algorithm that does the choice, as suggested by Intuitionism (Fehlmann & Kranich 2020). This is counter-intuitive to human perception of the world but reflects the standpoint of mathematical logic (Fehlmann & Kranich 2020). It enables intelligent systems to behave truly reasonable and rationally.

Research Questions

Regarding question 1, we proposed a theoretical foundation for AI which is not new but rather based on ideas from Rosenblatt, Scott, and Engeler.

With concepts, we can build intelligent systems that behave predictably when able to apply the right concept. Testing such systems, or relying on such systems, is easier than with traditional model-based AI. You not only can do black-box testing but, using concepts, you can even perform white-box tests. This is a big advantage if intelligent systems should become accountable for social and environmental well-being. The answer to research question 2 is affirmative.

Regarding question 3, how should intelligent systems evolve, we answer by referring to DevOps as the development methodology of choice to enable intelligent systems.

The answer to research question 4, will intelligent systems ever be able to solve unfamiliar problems on their own, must remain open. Although Engeler (2019) describes a class of combinators in his neural algebra that accomplish such creative work, the practical proof is yet open.

Also, recent experiences with AI (Panigrahi et al. 2023) suggest a positive answer, at least for LLM that are big enough, but more work in the direction of Turing (1937) and Chollet (2019), who devised some sort of intelligence quotient test for AI, is needed.

What can be concluded, is that adapting the von Neumann principle to AI, representing knowledge by combinators and use a common framework, the arrow terms, to represent both knowledge and programs, yields a wide range of possibilities and new opportunities (Copeland 2006).

Open Questions

How to program concepts exactly?

Lisp, Scala, others?
How to link program code to observed objects (grounding)?

What is the cost function for combining concepts?

Functional size?
Reliability of the AI machine learning process?

Will AI machines eventually program themselves?

Is DevOps just a temporary solution?
Will DevOps become unnecessary for AI?
Do fixpoints help focusing (Fehlmann & Kranich 2022)?

How to protect the freedom of citizens against AI?

What about Security & Privacy?
How to test concepts for compliance?

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Exploring UNFCCC's Market-based Climate Interventions in Kenya's Large-scale Renewable Energy Market

By Chigozie Nweke-Eze[*]

The past decades have seen a general embrace of market-based approaches and instruments in governing all manner of socio-economic concerns. The environment is not excluded. Since the 1980s, market-based environmental governance has become popular in tackling issues ranging from climate change and resource depletion to biodiversity loss. This paper explores the structural conditions that shape such market interventions in environmental governance. More specifically, it analyses the assemblage of different forms and mechanisms of market intervening actions in today's renewable energy markets by drawing on Michel Foucault's structural formulation on free-market governance. The paper shows that while Foucault's formulation on market intervening actions (consisting of "regulatory" and "organizing" actions) still has merit in contemporary market governance, its application has become less encompassing. The Foucauldian formulation has largely left out an important category of market interventions that is mainly financial in nature. In recent decades, such financial interventions have increasingly acted as catalysts for better market efficiency – especially in developing markets – acting in closer proximity to the market than regulatory and organizing actions. The paper elaborates this new category of intervening actions as "catalyzing" actions. For illustration, the paper applies the more complete formulation on market intervening actions in analyzing UNFCCC's climate governance and financing interventions in Kenya's large-scale renewable energy market. The analysis on data from expert interviews with actors in the energy, environment, and financial management sectors in Kenya, as well as on document and reports analysis.

Keywords: *UNFCCC, Market-based Interventions, Foucault, Climate governance, Financing, Renewable Energy Markets, Kenya*

Introduction

The past decades have seen a general embrace of market-based approaches and instruments in governing all manner of socio-economic concerns (Berndt et al. 2020). This turn to the market manifests in the widespread prioritization of private property and individual self-interest as the most effective means of ensuring efficient resource allocation (Peck et al. 2020). The environment is not excluded from this approach of governance. Since the 1980s, market-based environmental governance has become popular in tackling issues ranging from climate change and resource depletion to biodiversity loss. This development has led scholars in geography and related fields, to theorize and debate the *neoliberalization of nature* (Bakker 2010, Bigger et al. 2018). By neoliberal natures, they refer to the

[*]Research Fellow, University of Bonn, Germany.

intersection of neoliberalism with the environment (Lave 2012), and more specifically, the commodification, marketization, and financialization of the environment as manifest in projects, programs, and policies (Christophers et al. 2018, Ouma et al. 2018, Asiyanbi 2018; Bridge et al. 2019, Bracking 2019, Bigger and Millington 2020). This increasing application of market logics in environmental projects and programs is largely welcome in the international development sphere and framed as the 'greening' of capitalism, i.e., the pursuit of economic growth in tandem with preserving the environment (Newell and Paterson 2010, Newell 2011). However, critical geographers, so far, see these market interventions in environmental governance as mostly ineffectual in driving the market to achieve its aims (Fletcher and Breitling 2012, Bracking 2014, 2015, Asiyanbi 2018, Bridge et al. 2019), and view their continued adoption and application to be for lack of other viable alternatives (Bracking 2019, Bigger and Millington 2020).

Notwithstanding the importance of this debate, this paper does not seek to rehash it. It rather focuses on the structural conditions that shape market interventions in environmental governance (Knox-Hayes 2016). More specifically, the paper explores the assemblage of different forms and mechanisms of market intervening actions in today's capitalist economies by drawing on Michel Foucault's structural analysis of free-market governance. The paper contends that although Foucault's formulation on market intervening actions (consisting of regulatory and organizing actions) still applies in contemporary market governance, its application has become less encompassing. It argues that the Foucauldian formulation has largely left out an important category of market interventions that is mainly financial in nature. In recent decades, such financial interventions have increasingly acted as a catalyst for better market efficiency and acted in closer proximity to the market than regulatory and organizing actions. The paper elaborates this new category of intervening actions as "catalyzing actions".

For illustration, the paper applies the more complete formulation on market intervening actions in analyzing UNFCCC's interventions in Kenya's large-scale renewable energy[1] market. Kenya's energy market has become more vibrant in recent years, involving more and diverse national and international investors, with a significant increase in generation capacity from about 1,600 MW in 2008 to 2819 MW in 2019 (IEA 2019, Klagge and Nweke-Eze 2020). This substantial improvement in the country's energy sector is a result of accelerated development of large-scale renewable energies in the country, partly driven by commitments, frameworks, and financing under the UNFCCC, in addition to state interventions in form of favorable laws, market incentives, and risk mitigation financing (GoK 2018, Klagge and Nweke-Eze 2020, Klagge 2021). The paper bases its analyses on data from expert interviews with actors in the energy, environment, and financial management sectors in Kenya[2], as well as from content analysis of various related documents[3].

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[1]The paper defines renewable energies as large-scale that have more than 25MW total capacity.
[2]A total number of 41 in-person key informant interviews was carried out in Kenya between February-March and August-September 2019; and between February-March, 2020. 21 of the key informants work at national agencies and parastatals (National Treasury (NT), Ministry of Environment and Natural Resources (MoEN), Ministry of Energy (MoE), National Environment

The rest of the article is divided into four sections. The first section discusses and extends Foucault's analyses on market intervening actions to include catalyzing actions. The section that follows sets the scene by discussing UNFCCC's market-based governance mechanisms in climate mitigation, as well as the Kenyan large-scale renewable energy market. The penultimate section applies the more complete formulation on market intervening actions in analyzing UNFCCC's climate mitigation interventions in Kenya's large-scale renewable energy market. In the conclusion, the paper reflects on its findings and their implications for discourses on market intervention mechanisms (Fletcher and Breitling 2012, Milne and Adams 2012, Fletcher 2013, Asiyanbi 2018), as well as on the growing importance of finance, even in climate change (Knox-Hayes 2016, Christophers et al. 2018, Bracking and Leffel 2021).

Conceptualizing Market Intervening Actions Beyond Foucault

Foucault and Intervening Actions in Capitalist Economies

Capitalist economies take the view that markets are best suited to allocate the economy's scarce resources. These economies leave such important elements as price-setting and other activities freely to the inter-play between the market forces of demand and supply. Foucault in his "The Birth of Biopolitics" (2008), complementarily reveals that the establishment and sustenance of an efficiently working market economy require active government interventions. These interventions, according to him, will in fact "*make the market work*" (Foucault 2008, p. 146). To demonstrate how the understanding of free-market ideology has been misconstrued by its critics (for example, McNally 2006), Foucault states that the proponents of the free-market economy (including Hayek and Friedman) never intended for markets to be understood as natural constructs (Foucault 2008). He rather argues that the market was rather fundamentally intended as artificial constructs of the state, constantly molded and re-molded through diverse forms of intervening actions (Peters 2006, Foucault 2008, Fletcher 2013). He delineated these intervening actions as "regulatory actions" and "organizing actions" (Foucault 2008, p. 138).

According to Foucault, regulatory actions are interventions on the economic processes of the market (2008). This set of actions are aligned to indirectly avert

Management Authority (NEMA)). 7 work in Development Finance Institutions ((DFIs), Trade and Development Bank (TDB), African Development Bank (AfDB), European Investment Bank (EIB), German Development Bank (KfW)). 11 of them work in the two main private and public renewable project development companies ((PDs) in Kenya (Kenya Electricity Generation Company (KenGen), Geothermal Development Company (GDC)); and 2 work as independent consultants (ICs) in energy and environmental sectors in the country.

[3]Analyzed documents include the National Climate Change Action Plan (Kenya): 2018-2022 (GoK 2018); the National Climate Change Framework Policy (GoK 2016a); the Climate Change Act (GoK 2016b); the National Policy on Climate Finance (GoK 2016c); and the Paris Agreement (UN 2015).

the market's erroneous tendencies and to ensure price stabilization (Foucault 2008, Fletcher 2013). Typical of such regulatory actions is the control of instruments such as maintaining credit balance when attempting to act on foreign prices; or controlling taxation, when attempting to act on savings and investments (Peters 2006, Foucault 2008, Fergusson 2010). Foucault further clarifies that such actions will not include instruments such as price controls, partial support of a market sector, or systematic job creation and public expenditure, which act directly on the market, creating a distortion (Foucault 2008, Fletcher 2013). Using the example of unemployment to illustrate regulatory actions Foucault writes (Foucault 2008, p. 139):

> "Whatever the rate of unemployment, in a situation of unemployment you absolutely must not intervene directly or in the first place on the unemployment…. What is to be saved, first of all and above all, is the stability of prices. Price stability will in fact allow, subsequently no doubt, both the maintenance of purchasing power and the existence of a higher level of employment…."

Here, he implies that given a market imperfection of unemployment, the conditions of the market to be acted on should be price stability, which has no direct effect on the mechanisms of the market (purchasing power and employment level), but which has an influential potential to bring the market back to balance (that is, to correct unemployment).

Turning to organizing actions, Foucault delineates them from regulatory actions by referring to them as acting on the conditions surrounding the market – on "*more fundamental, structural and general*" aspects of the market (Foucault 2008, p. 141). In this sense, organizing actions, essentially include a whole range of social and legal systems, technological enablement, and ecological parameters that are geared towards stimulating markets (Foucault 2008, Asiyanbi 2018). In contrast to regulatory actions, the intervening roles of organizing actions are more substantial and direct, and requiring heavier government interventionism (Foucault 2008, Fletcher 2013). Using the case of the German early 1950s agricultural market to illustrate organizing actions, Foucault writes:

> "So on what will it be necessary to act [on for the correction of the market's imperfection and maximization of its potentials]? Not on prices, and certainly not on a particular sector, ensuring support for a scarcely profitable sector, since these are bad interventions… [but on] population, technology, training and education, the legal system, the availability of land, the climate [which] are directly economic and do not affect market mechanisms directly" (Foucault 2008, pp. 140-141).

According to Foucault, these state interventions should however always remain within the confines of shaping the conditions of the market and never on the mechanism of the market itself – not on the game itself but on the "*rules of the game*" (Foucault 2008, p. 174). These actions are supposed to be neither planned nor targeted for specific outcomes in the market – he in fact calls them the "*opposite of a plan*" (Foucault 2008, p. 172). They should rather be directed towards creating enabling market environments, structures and incentives, necessary for the efficient interaction of the market forces to allow for more efficient allocation of resources (Fletcher 2013, Asiyanbi 2018).

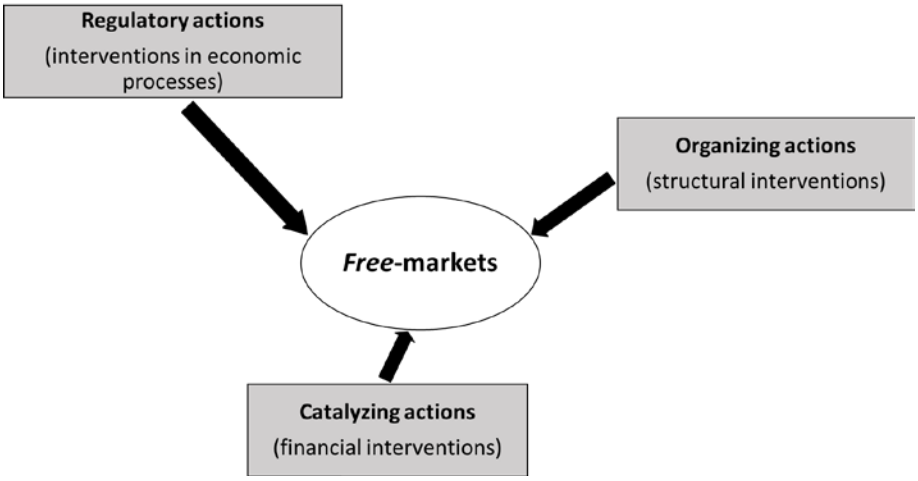
Extending Foucauldian Market Intervening Actions

During the postwar period about which Foucault was writing, markets were still dominated by real commodities and there were lesser ways in which finance was put to use. Finance had not yet come to prominence and dominance, as we know it today – shifting modes of production and aligning markets to sustainable development priorities, all of which are achieved through constant dismantling and assemblage of market logics and actors (Baker 2015, Newell and Phillips 2016, O'Brien et al. 2019). It has therefore become pertinent to stretch Foucault's delineation of market intervening actions ("regulatory" and "organizing" actions) to include what the paper calls "catalyzing actions". Catalyzing actions, here, refer to various financing interventions on the conditions of the market, available in forms of equity, loans, grants, guarantees, mezzanine, bonds, and other securities. They perform roles of market incentivization and risk mitigation, which are of particular importance in risky and capital-intensive markets, for market optimization. In this sense, catalyzing actions operate in closer proximity to the market than organizing and regulatory actions.

In recent decades, catalyzing actions have been crucial to the expansion of capitalism and industrialization, as well as in advancing government programs and causes in the broad areas of development and environment (OECD 2014, Schwerhoff and Sy 2017). In today's market economy, catalyzing actions have also taken up new forms and roles in influencing the market for desirable economic, social, political, and environmental outcomes. They have taken up the form of blended-finance, where financing of "worthy" capital projects are made cheaper through the blending of loans and grants – a practice which has become common in international development financing (Mawdsley 2018, Strand 2019, Rode et al. 2019, Christiansen 2021, Bracking and Leffel 2021). They are deployed in form of risk guarantees intended to strategically smoothen out uncertainties, which may hinder further investments in the market, by taking up costs of foreseen riskier aspects of market development and/or promising to take up unforeseen ones (Wüstenhagen and Menichetti 2012, Klagge 2021). They are also increasingly deployed in form of reparations or compensations, to make up for inevitable social and environmental losses to allow for certain other economic projects and agendas, which are perceived to be of "greater good" to carry on (Segovia 2006, Castán et al. 2016, Kenney-Lazar 2018). Furthermore, over the recent years, catalyzing actions and their logic have continued to permeate the market, through their increasing applications and dominance – a phenomenon that has been termed financialization (Pike and Pollard 2010, Christophers 2012, Bracking 2019).

Figure 1 summarizes the extended market intervening actions in capitalist economies. The figure also depicts the proximities of these interventions to the market, using the length of the connecting arrows. Catalyzing actions are depicted to be of the closest proximity to the market, followed by organizing actions, and then regulatory actions.

Figure 1. *Forms of Market Intervening Actions in Capitalist Economies*



UNFCCC and the Kenyan Large-scale Renewable Energy Market

UNFCCC's Market-based Governance Mechanisms in Climate Mitigation

In order to enforce its climate mitigation mandates contained in its Kyoto Protocol and Paris Agreement, the United Nations Framework Convention on Climate Change (UNFCCC) created market-based mechanisms and instruments, through which it increasingly continues to intervene in climate-related markets, seeking to enforce its agenda for reducing GHG emissions in the earth's atmosphere. One of such mechanisms can be grouped as Specialized Funds. Specialized funds were created through funds pulled from developed countries in the Global North for assisting developing countries of the Global South in financing their climate mitigation and adaptation projects and activities, all in compliance with emission reduction commitments (Watson and Schalatek 2019, Bertilsson and Thorn 2020). The largest of such funds is the Green Environmental Facility (GEF), created in 1991, which provides upfront funding, in co-financing arrangements with Development Financial Institutions (DFIs) and other public organizations, for climate mitigation or adaptation projects and programs in the Global South (GEF 2010, Graham 2017, GEF website 2020). Another more recent Specialized Fund under the UNFCCC is the Green Climate Funds (GCF), which was instituted in 2010 as a major effort to increase the funding base for the financing of climate mitigation and adaptation projects in developing countries (Bracking 2014, Bertilsson and Thorn 2020, GCF website 2021). GCF provides funds for enhancing climate projects, policies, programs, and activities according to its established themes (Bruun 2017, GCF website 2021). These Specialized Funds are accessed via competitive application processes, which are organized and administered at the national level of recipient countries by selected National Designated Authorities (NDAs) (Bracking 2014, NT and MoEN interviews 2019, GEF and GCF websites 2020). Despite the growing financial base of Specialized Funds, their efficacy and impacts in incrementally achieving their goals in the

Global South remain debatable (Kasdan et al. 2018, Puri 2018, Kuhl and Kurukulasuriya 2020, Bracking 2021).

A more market-orientated mechanism created by the UNFCCC is the Clean Development Mechanism (CDM), created under the Kyoto protocol in 2006, with the dual role of assisting developing countries in achieving sustainable development, while helping industrialized countries in fulfilling their climate mitigation commitments (UNFCCC 2019)[4]. The CDM functions through the commodification and marketization of carbon for gaining carbon credits (formally called certified emission reduction (CERs), trading at 1 CER = 1 metric tonne of CO_2 (UNFCCC 2019). This process of carbon commodification and marketization has attracted research that underpin the creation of markets and the growing roles of nature as an accumulation strategy (Smith 2006, Bumpus and Liverman 2008, Bridge et al. 2019), highlighting how carbon's commodification has created opportunities for finance capital, and its attendant financial actor constellation and financialization (Knox-Hayes 2016, Bigger 2016). Such research also highlights how such accumulations are enabled at the expense of the livelihood of landscape and communities in the space where carbon offset is created (Paterson 2010, Bumpus and Liverman 2011). CDM's inefficacy in achieving its goals especially in countries of the Global South is attributed to its slow, long, and complex bureaucratic processes, late and delayed CDM revenues, subjective additionality criterion, distorted credit prices (Spalding-Fetcher et al. 2012, Wood et al. 2016). As a result of CDM inefficiencies and its subsequent collapse, it was replaced in 2016 by a new international carbon market under the Paris Agreement of the UNFCCC, called the "Sustainable Development Mechanism". This new carbon market is primarily designed to raise further ambitions based on voluntary participation (UN, 2015). Unlike CDM, it will account for only one country's emission reduction targets in any given carbon-trading encounter, thereby avoiding the risk of double counting (Article 6(2), UN 2015).

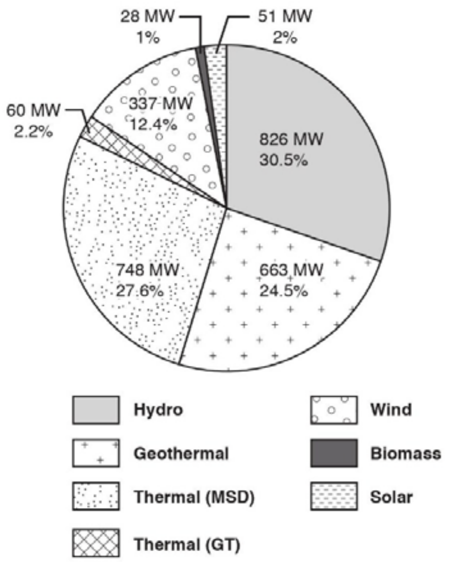
Overall, the UNFCCC, with its pragmatic governance approach and interventions in climate-related markets, typifies the growing number of institutions with such growing application of market logics of competitive bidding, commodification, marketization, and financialization in environmental governance (Bäckstrand and Kuyper 2017, Hickmann et al. 2021). With its international legitimacy and institutional resources, the UNFCCC sets agendas; and through negotiations, agreements, and commitments, it establishes baselines upon which to intervene in manipulating climate change indicators (rates of GHG emissions) so as to sustain the environment and life as a whole (Pattberg and Widerberg 2015). In this sense, the UNFCCC governance approach lends itself to a Foucauldian understanding of the development and expansion of market-based approaches to environmental governance (Peters 2006, Fletcher 2013 Asiyanbi 2018).

[4]For recent regional data on CDM market activities, see the CDM market insight briefing from Ecosystem Marketplace (Donofrio et al. 2021).

Kenya's Large-scale Renewable Energy Market

Large-scale renewable energies currently dominate Kenya's electricity grid, accounting for more than 70% of installed electricity production (see Figure 2). The capacity contributions of these renewable energies to the electricity grid have boosted the country's electricity access rate in recent years, with the number of connected households increasing from 32% in 2013 to 75% in 2018[5] (IEA, 2019; MoE interviews 2019).

Figure 2. *Pie Chart Showing the Installed Electricity Generation Mix in Kenya (2019)*



Source: Author's own, generated from IEA data (2019), and validated with interview data from the Kenyan Ministry of Energy (MoE 2019).

Kenya plans to build further on these efforts in line with its UNFCCC commitments (GoK 2016d, 2018). In its socio-economic development roadmaps, the country expresses its desire to increase its installed electricity capacity by an additional 2700MW, mainly from "clean and sustainable sources" (GoK 2007, 2016d, MoE interviews 2019, 2020). To this end, large-scale renewable energy development has come to the forefront of Kenya's climate mitigation efforts as well as its efforts to increase its electricity generation capacities (MoE interviews 2019, 2020). To fast track the achievement of these goals, the Kenyan state created Special Purpose Vehicles (SPVs) to drive and support the development of

[5]Most of this electricity access was achieved through the government's Last Mile Connectivity Program – an initiative that sort to extend the electricity grids to rural, previously marginalized areas of the country (MoE interviews 2019, 2020). Connection to the grid, through this program does not, however, guarantee actual use of electricity in all regions of the country. Factors such as unreliability of power supply (frequent blackouts) and affordability of power and appliances prevent some households, especially in rural areas, from using connected electricity (MoE interviews 2020, also see Lee et al. 2020).

renewable energy potentials in the country by taking up risks and providing market incentives in order to attract more financing from the public and private sector investors at international and national levels (MoE and NT interviews 2019). Two of such SPVs are the Geothermal Development Company (GDC), with the mandate of conducting explorations and other initial developments of geothermal fields in the country, and the Rural Electrification and Renewable Energy Corporation (REREC, formerly called Rural Electrification Agency (REA)), which is charged with expanding electricity access to rural areas using mainly renewable energy technologies (MoE interviews 2019, 2020). As a result of these state efforts, combined with technical and financial interventions from international Development Financial Institutions (DFI) and the UNFCCC – through its market-based mechanisms, several large-scale renewable energy projects utilizing the country's geothermal, wind, solar, hydro, and biomass resources are currently ongoing in the country, while others are already completed (see Table 1).

UNFCCC's Intervening Actions in Kenya's Large-scale Renewable Energy Market

Over the recent years, Kenya has increasingly adopted UNFCCC interventions in its climate mitigation efforts, especially in large-scale renewable energy markets, as part of a broader initiative to boost the country's energy sector development. (GoK 2018, MoEN, MoE, NT interviews 2019). The sub-sections that follow explain how these UNFCCC interventions (commitments, frameworks, and financing) can be interpreted in the light of the expanded market interventions formulation (regulatory, organizing, and catalyzing actions).

Table 1. *Projects and Intervening Actors in the Kenyan Large-scale Renewable Energy Market*

Renewable energy types	Projects	Project status and years	Capacity in MWs	Developers & investors	Intervening international development institutions and programs	UNFCCC's Intervening mechanisms
Geothermal	Olkaria I, II, III, IV, V, VI	Partly completed in 2015, other constructions ongoing	185	KenGen (70% GoK-owned)	EIB, JICA, IDA, AFD & KfW	GEF, GCF, CDM.
	Menengai I	Under construction since 2011	105	GDC, Ormat, Symbion & Sivicon	AfDB, AFD, EIB, USTDA; PPIAF, SREP	GEF, GCF.
	Baringo-Silali	Under construction since 2018	n.a	GDC	KfW, GRMF	GEF, GCF.
Wind	Lake Turkana Wind Power (LTWP)	Completed in 2018	310	LTWP Ltd	AfDB, EIB, EKF, FMO, EADB, TDB, PROPARCO, ICCF, EU-AITF	GEF
	Ngong wind	Completed in 2015	25.5	KenGen	--	GEF, CDM
	Kipeto wind	Under construction since 2018	100	KEL	OPIC	CDM
Solar	Garissa	Completed in 2018	54.6	REREC	Exim Bank of China	GEF, GCF
	Alten Kesses 1	Under construction since 2013	55	Alten	Standard Bank of South Africa, Stanbic and EAIF	GEF
Hydro	Tana	Completed in 2010	67.7	KenGen	--	GEF, CDM
	Kiambere	Completed in 2009	82.5	KenGen	World Bank	GEF, CDM.
Biomass	Mumias Sugar	Completed in 2008	35	Mumias Sugar Co. ltd	PROPARCO	GEF, CDM.

Explanation of abbreviations:

Developers/Investors: KenGen = Kenya Electricity Generation Company. LTWP= Lake Turkana Wind Power. KEL= Kipeto Energy Ltd. GDC =Geothermal Development Company. GoK = Government of Kenya.

Intervening international development institutions and programs: AFD = Agence Française de Développement (the French government-owned development bank). AfDB = African Development Bank. EADB = East African Development Bank. EAIF = Emerging Africa Infrastructure Fund. EIB = European Investment Bank. EKF = Danish Export Credit Agency. EU-AITF = EU-Africa Infrastructure Trust Fund. EXIM Bank of China = Export and Import Bank of China. FMO = Dutch Entrepreneurial development bank. GRMF = Geothermal Risk Mitigation Facility. ICCF = Interact Climate Change Facility. IDA = International Development Association. JICA = Japan International Cooperation Agency. KfW = Kreditanstalt für Wiederaufbau (the German government-owned development bank). OPIC= Overseas Private Investment Corporation (US government's development financial institution). PPIAF = Public Private Infrastructure Advisory Facility. PROPARCO = subsidiary of AFD focused on private sector development. SREP = Scaling-up Renewable Energy Program. TDB = Trade and Development Bank (mainly of member countries in East and Southern Africa). USTDA = U.S. Trade and Development Agency.

UNFCCC's intervening mechanisms: GEF = Green Environment Fund. GCF = Green Climate Fund. CDM = Clean Development Mechanism.

Source: Author's own, generated from Project official websites as at 10-May-2020, and complemented and validated with various interview information, 2019/2020.

UNFCCC Commitments as Regulatory Actions

The UNFCCC, through its commitments, indirectly structures the behavior of constituent parties by providing shared signification to stabilize greenhouse gas (GHG) emissions in the atmosphere through climate mitigation actions. Kenya, despite its negligible contribution to GHG emissions (less than 0.1% in 2018), shares many of these commitments because it sees them as being in line with its national interests for sustainable development (MoE, NT, MoEN interviews, 2019). These commitments, especially with regards to climate mitigation, are embedded in the country's medium and long-term development plans, officially called Medium Term Plans (MTPs) and Vision 2030, respectively (GoK 2007, 2016d, MoE, MoEN interviews 2019). The Kenyan Vision 2030 states that Kenya aspires to be "*a newly industrializing, middle-income country providing a high quality of life of its citizens by 2030 in a clean and secure environment*" (GoK 2007). In its Nationally Determined Contributions (NDC), ratified under the Paris Agreement, Kenya committed to achieving a GHG emission reduction contribution of 30% amounting to 42.9 MtCO2e of net emission reduction, relative to the baseline of 143MtCO2e, by 2030 (GoK 2018, MoEN interviews 2019). In its newly submitted NDC (2021), the country increased its GHG reduction contribution pledge[6] to 32% (that is, to 46 MtCO2e) (GoK 2021). For meeting these targets, the country prioritizes increasing the share of renewables energies in its electricity generation mix (GoK 2010, 2016a, 2018, MoE, MoEN interviews 2019). On the rationale for the country's prioritization of large-scale renewable energies in its climate mitigation efforts, an interviewed director of climate change at the MoEN states:

> "The capacity of these projects [large-scale renewable energy projects] to reduce emissions is huge, it happens in a snap. Once the project is online, you start counting emissions reduction, whether it is going towards the carbon markets or it is going towards achieving our NDC [Nationally Determined Contribution]. The emission reductions are real, and they are much easier to monitor, compared to other sectors."

To vitalize its renewable energy market for meeting these climate mitigation commitments, the Kenyan government implemented several investment-friendly policies and incentives at both national and sub-national levels. These include policies on Feed-in-Tariffs (FiTs), the waving or reduction of duties for imported renewable energy technologies, as well as tax holidays for large-scale renewable energy project developers (MoE, NT, PDs, DFIs interviews 2019). Furthermore, the state also provided "bankable" power purchase agreement (PPA) frameworks, electricity off-take assurances, and good regulatory institutions – all of which are directed towards encouraging adoption and development of renewable energy technologies on large scales (MoE, NT, PDs & DFIs interviews 2019). On

[6] In meeting these targets, the country promised to take up 21% of the mitigation costs, while the remaining 79% is subject to international support in form of finance, technology development and transfer, and capacity building (GoK 2021).

Kenya's success in providing enabling environment for its renewable energy market vitalization, the interview partner at the Trade and Development Bank (TDB) elaborates:

> "… The effort on the government side is huge in creating enabling environment for people to develop, adopt and access renewable energies. As a result, investors' attraction is just amazing. So many investors are looking into investing in the energy sector, especially the generation of electricity. Kenya is quite competitive, you find the EIB [European Investment Bank], the World Bank …the attraction is just massive. And you know, this competition amongst different financiers brings down the cost of borrowing for renewable energy projects."

UNFCCC Frameworks as Organizing Actions

Following its ratification of the UNFCCC's Paris Agreement in 2016, Kenya enacted its Climate Change Act (2016) – a legal apparatus that guides and coordinates national efforts towards addressing climate change in the country (GoK 2016b, MoEN interviews 2019). The Climate Change Act (2016) establishes the National Climate Change Council (NCCC), as the highest body responsible for oversight and coordination, and the Climate Change Directorate (CCD) as the secretariat of the NCCC responsible for the technical aspects (measurements, monitoring, reporting and capacity building support) of the implementation of its climate change agenda at national and sub-national levels. The Climate Change Act further made provision for the formulation of the National Climate Change Action Plan (NCCAP), which is a five-year plan that stipulates guidelines for integrating and mainstreaming UNFCCC climate actions in all sectors of the national economy including the County Integrated Development Plans (CIDPs) at sub-national levels (GoK 2016a & b, GoK 2018, MoEN interviews 2019). To further organize and coordinate UNFCCC interventions at multi-governmental levels in Kenya's large-scale renewable energy market, the Ministry of Environment and Natural resources (through its related parastatals, such as the National Environment Management Agency (NEMA)), and the National Treasury (Kenya's equivalence for Ministry of Finance) act as *linking institutions* between the UNFCCC and the government of Kenya. They do this by acting as National Designated Authorities (NDAs) in organizing climate mitigation actions in Kenya. To optimize their performance, staff members from these linking institutions periodically receive short-course training and orientations in the management and administration of UNFCCC mechanisms. On these training, an interviewed policy advisor working at the National Treasury explained:

> "We receive several capacity-building trainings from the UNFCCC. It is a continuous process. We had one in May and June, we will be going for another one next week, and other ones are planned in the future – so it is a continuous process. The training usually starts with introductory aspects to climate change, and then goes to its response and governing mechanisms. The Ministry of Environment and Natural Resources and the National Treasury often take part in these training, at the national level. Afterward we then train other ministries at national and county [sub-national] levels – that is why it [the training] is often called, Training of Trainers [ToT]."

Many of the interview partners believe that these skills, acquired through training received by UNFCCC staff members, will not only serve their intended purposes but will be transferred to the governance of subsequent market-based environmental mechanisms in the country. As the interview partner at the MoEN explained:

> "Yes, the Kyoto Protocol is ending in 2020, but it came with a lot of learning and experience for us. These lessons will be transferred into the Paris Agreement and other subsequent ones. We cannot throw the baby out with the bathwater. So yes, the window might close on the Kyoto Protocol but the lessons from it, especially with the carbon trading, will be carried on into new agreements."

UNFCCC Financing as Catalyzing Actions

Climate financing, under the UNFCCC, is an important catalyzing action in Kenya's large-scale renewable energy market (GoK 2016c, NT, MoE, MoEN interviews 2019). Kenya strategically uses financing from Specialized Funds (the Green Environmental Facility (GEF) and the Green Climate Fund (GCF)), as well as from the Clean Development Mechanism (CDM) to mitigate risks and crowd-in investors at different development stages of large-scale renewable energy projects in Kenya (GoK 2016c, NT, DFIs interviews 2019). Financing from the Specialized Funds are targeted and role-specific, flowing through various implementing and accredited agencies, including international development financial institutions such as the World Bank, and the European Investment Bank (EIB), as well as through international private banks, such as the Deutsche Bank (see Tables 2-3).

Table 2. *Approved and Funded GEF Projects and Programs Relating to Large-scale Renewable Energies in Kenya (1991-2019)*

Project/Program Title	**Grant & Co-financing**	**Implementing Agencies**	**Other beneficiary countries**	**Periods**
Sustainable Conversion of Waste to Clean Energy for Greenhouse Gas (GHG) Emissions Reduction	$1,999,998 $9,824,718	UNIDO	---	GEF-5
SolarChill Development, Testing and Technology Transfer Outreach	$2,712,150 $8,033,500	UNEP	Colombia, Eswatini	GEF-5
Lighting the "Bottom of the Pyramid"	$5,400,000 $6,750,000	The World Bank	Ghana	GEF-3
African Rift Geothermal Development Facility (ARGeo)	$4,750,000 $74,261,652	UNEP	Eritrea, Ethiopia, Rwanda, Tanzania, Uganda	GEF-3
Joint Geophysical Imaging (JGI) Methodology for Geothermal Reservoir Assessment	$979,059 $0	UNEP	---	GEF-3
Building Sustainable Commercial Dissemination Networks for Household PV Systems in Eastern Africa	$693,600 $0	UNEP	Eritrea, Ethiopia, Tanzania, Uganda	GEF-3
Solar and Wind Energy Resource Assessment	$6,512,000 $2,508,000	UNEP	Multiple countries	GEF-2
Photovoltaic Market Transformation Initiative	$30,000,000 $90,000,000	IFC	India, Morocco	GEF-1

Explanation of abbreviations: IFC = International Finance Corporation UNIDO = United Nations Industrial Development Organization. UNEP = United Nations Environment Programme.
Source: Author's own, compiled from GEF project database (2020); complemented and validated with interview information (2019).

Table 3. *Approved and Funded GCF Projects and Programs Relating to Large-scale Renewable Energies in Kenya (2010-2019)*

Project/Program Title	**Total Project Investment (million USD)**	**Accredited Entity (AE)/ Delivery Partner**	**Lead Executing Entity (EE)**	**Other beneficiary countires**
Global Energy Efficiency and Renewable Energy Fund (GEERF) NeXt	765	EIB	Ministry of Energy	Multiple countries
KawiSafi Ventures Fund	110	Acumen Fund Inc.	Acumen Capital Partners LLC.	Rwanda
The Universal Green Energy Access Program (UGEAP)	301.6	Deutsche Bank	Ministry of Energy	Kenya, Benin, Namibia, Nigeria, Tanzania
Climate Investor One (CIO)	821.5	FMO	Local financial partners	Multiple countries
Transforming Financial Systems for Climate (TFSC)	745	AFD	Local financial partners	Multiple countries

Explanation of abbreviations: EIB = European Investment Bank. AFD = Agence Française de Développement (the French government-owned development bank).
Source: Author's own, complied from GCF project database (2020); complemented and validated with interview information 2019.

At the pre-completion stages of renewable energy projects development, climate financing from the Specialized Funds is used to cover cost-intensive and risky activities of the projects' development, mainly relating to project feasibility studies, resource prospecting and exploration, training of staff, and the procurement of certain heavy equipment in cooperation with the project developers (see Tables 2-3). This financing help to mitigate investment risks that would otherwise be passed on to investors and project financiers (MoE, DFIs interviews 2019), making projects more appealing to investors, especially private sector developers and investors, who are then more confident to participate in the market (GDC, NT interviews 2019). In addition to its risk-mitigation roles, the financing from the Specialized Funds also served as debt-blending instruments, as they were issued as concessionary funds in combination with loans from Development Financial Institutions (DFIs), thereby lowering the final debt costs for borrowing project developers and investors (DFIs interviews 2019). The provision of these climate financing, as both debt-blending instruments and grants, facilitated the completion and commissioning of the many large-scale renewable energy projects in the country (PDs, NT, DFIs, and MoE interviews 2019). On the effectiveness of climate financing as blending instruments in Kenya's large-scale renewable energy market, an interviewed energy project-financing specialist at the Trade and Development Bank (TDB) explains:

"Our treasury is always pushing us to get a 'renewable energy pipeline'. Although the projects are riskier, we find other strategic initiatives in the bank, like the blending instrument. What we are doing with 'blending' is that we get a pool of concessionary funds from the GCF [Green Climate Fund], for instance, that we can blend with our market debt – so that the final cost to the borrower becomes very low. …Like the transaction we did with ADB [Asian Development Bank], the CTF [Clean Technology Fund] brought in US$20 million into the transaction, at the pricing of just approximately 0.75% per annum. Other lenders – ADB, Finnfund, and our loans were priced high. But when we combined it with the cheap climate financing and worked out the weighted average cost, the debt financing became very attractive to the developer, the tariff was very competitive."

At post-completion projects stages, developers who had registered their projects with the UNFCCC's Clean Development Mechanism (CDM) in their pre-completion phases become eligible to earn carbon credits upon completion of the projects. In Kenya, large-scale renewable firms – Kenya Electricity Generating Company PLC (KenGen – a 70% government-owned company) and Mumias Sugar Company (a privately owned company), are among the beneficiaries of financing under this mechanism. So far, KenGen has registered three geothermal, one wind, and two hydro projects totaling about 1.4billion tCO_2 (KenGen interviews 2019; see Table 4).

Table 4. *Large-scale Renewable Energy Projects in Kenya Registered under CDM (2008-2019)*

Projects	Renewable Energy Type	Capacity (MW)	Date of registration	Start of Crediting Period	Estimated tCO_2 equiv/year	Estimated Cumulative CER's up to 2020 tCO2 equiv (USD)
Mumias Sugar	Biomass	35	03-Sep-08	01-Oct-08	129,591.00	24.418.20
Olkaria II*	Geothermal	35	4-Dec-10	4-Dec-10	149,632.00	1,047,424.00
Tana	Hydro	19.6	11-Oct-11	11-Oct-11	25,680.00	231,120.00
Kiambere	Hydro	20	24-Oct-12	1-Nov-12	41,204.00	288,428.00
Ngong	Wind	5.1	19-May-14	1-Jul-14	9,941.00	59,646.00
Olkaria I, AU 4&5	Geothermal	140	28-Dec-12	1-Jan-15	635,049.00	3,810,294.00
Olkaria IV	Geothermal	140	28-Dec-12	1-Jul-14	651,349.00	3,908,094.00
Total					**1,512,855.00**	**9,345,006.00**

Source: UNFCCC (2020, CDM Registry); validated with interviews information (2019).

Following the signing of the Emission Reductions Purchase Agreement (ERPA) with the World Bank for the sale of the Olkaria II U3 CER, KenGen has so far earned US$225,000 (KenGen interviews 2019, UNFCCC 2020). Likewise, Mumias has also earned US$270,000 from the trade of carbon to Japan Carbon Finance Limited (JCF) (NEMA interviews 2019, UNFCCC 2020). These carbon credits earned through the trading of carbon reduces the cost of investment and adds to the profits of the developers and investors (NT, MoEN, KenGen interviews 2019).

The benefits of CDM in Kenya also transcends its benefits for the project developers and investors. CDM has also enabled the delivery of projects and other initiatives for the beneficiation of project-host and surrounding communities. Under the World Bank's Community Development Carbon Fund (CDCF), 10% of carbon credit revenues generated from Olkaria II geothermal projects CERs have been used to implement four projects for host and surrounding communities (Schade 2017, KenGen interviews 2019). They include classrooms, water pipelines, and water pans for domestic uses and for livestock (Schade 2017, KenGen interviews 2019). In the same vein, the construction of the Mumias Biomass electricity project has generated employment for host-community members as well as led to the expansion of electricity access to the rural community where the project is hosted (Schade 2017, NEMA interviews 2019).

In Kenya, however, accessing these UNFCCC financing at both the pre- and post-completion stages of the project is however not easy for the project developers and industry investors. It involves certain bureaucratic processes, which many of the applicants (project developers and investors) find complicated. As one of the interviewed staff members at the National Treasury (National Designated Authority for GCF accreditation) noted:

> "The GCF is a very bureaucratic institution with lots of developments here and there. It takes a lot of time before they issue accreditation".

Like the Specialized Funds, CDM uptake has also been somewhat limited in the Kenyan large-scale renewable energy market due to its many bureaucratic procedures and regulations. An interviewed KenGen's Chief Officer for Environment and CDM at that time of the company's CDM application describes the nature of complications in accessing carbon credits for the Olkaria geothermal energy project as follows:

> "During the first verification mission of the UNFCCC/CDM verifier to the Olkaria II expansion project, issues regarding the project boundary came up. The boundary issue revolved around the possibility of steam sharing between Olkaria I [a non-CDM registered project] and Olkaria II, Unit 3 [a CDM registered project]. To resolve this issue, we had to prove that the CDM project in Olkaria II did not compromise power generation in Olkaria I. To this effect, studies showing records of steam output from the wells supplying Olkaria I were provided, in addition to other studies. If it had been determined that the Olkaria II project negatively affected power generation and steam supply in Olkaria I, it would have meant that we will be forced to modify the project boundary in the registered CDM Project Design Documents (PDD) to include Olkaira I. The inclusion of Olkaria I in the project boundary would have increased monitoring and staffing requirements as well as caused further delay in issuance of the CERs [carbon credits]. The KenGen [the state-owned developer of the project] team worked closely with the World Bank Carbon Finance Unit to rectify this issue."

As the above paragraph also shows, challenges in accessing UNFCCC financing in Kenya's large-scale renewable market create "leveraging gaps", thereby creating room for further interventions by other actors (in the above case, the World Bank). Other than the intervening roles of the Development Financial Institutions (DFIs) in closing this climate finance leveraging gap, private for-profit firms have also emerged to play similar intervening roles, and by so doing have created room for the manifestation of financialization processes in UNFCCC's catalyzing actions in Kenya's large-scale renewable energy market (MoE and NT interviews 2019). These emerging financialized firms serve as consultants for accessing specialized climate funds or as carbon trading intermediaries, offering services to the Kenyan government agencies (National Designated Authorities) as well as to public and private sector renewable energy project developers and investors who are seeking to leverage climate finance (MoEN, NT, ICs interviews 2019). Prominent of such financialized firms in the Kenyan climate financing landscape is the English *ClimateCare* – a for-profit firm with headquarters in Oxford, which provides carbon-offset services to public and private actors in climate mitigation sectors of the country (NT and ICs interviews 2019).

Conclusion

This article engaged with a relatively less applied lens in market-based environmental governance, a Foucauldian formulation, to explore the question of market organization in contemporary capitalist economies. It stretches Foucault's formulations by bringing finance into the mix, proposing a new category of "catalyzing actions", in addition to Foucault's "organizing actions" and "regulatory actions". It goes on to substantiate its argument by applying the extended formulation on market intervening actions in analyzing UNFCCC's interventions in Kenya's large-scale renewable energy market. By so doing, the paper demonstrates how market intervening actions can be understood in a fuller context when the growing use and importance of finance as interventions in capitalist economies are considered. In this sense, a more complete conceptualization of market interventions in a capitalist economy then includes regulatory actions, which act in economic processes of the market in form of commitments and policies; organizing actions, which acts on structural conditions of the market in form of frameworks; and catalyzing actions, which act as market catalysts in form of financing. In considering the different, and sometimes coordinated, roles of these market-intervening actions, the paper shows how catalyzing actions are relatively more targeted as well as perform in closer proximity to the market in comparison with regulatory and organizing actions. This extended view on market-intervening actions is especially important in the Global South context, where financing increasingly plays important catalyzing roles in development endeavors, including in climate change.

The findings of the paper have wider implications in coordinating and appraising market-intervening tools in today's environmental governance. The achievement of market goals requires effective intervening actions from governing players at multi-levels (global, international, national, and sub-national levels) (Kuyper et al. 2017). It is, therefore, pertinent to understand these intervening actions – their mechanisms, processes, and roles in their fuller senses, to allow for better coordination, alignment, and appraisal in capitalist economies, especially in the Global South context (Zelli 2011, Kuyper et al. 2017). The paper, through the analysis of UNFCCC interventions in Kenya's large-scale renewable energy market, shows the mechanisms, roles, and processes in which multifaceted environmental interventions at global levels are implemented at national and sub-national levels, targeted towards reaching market goals (here, reducing GHG emission). In the Kenyan context, these global interventions are welcome at national levels insofar as they align with national interests. It is this perception, at the national level, that then brings about the dedicated implementation of interventions, with direct effects on climate mitigation, particularly in the renewable energy market sector of the country.

Furthermore, the findings of the study reveal how, in addition to their intended roles, these interventions play other roles that are unintended but with positive cascading effects in the market. For instance, the training and skills in project financing application, management, and evaluation, which are provided to the staff members of the UNFCCC Nationally Designated Agencies in the country, are applied beyond the achievement of their intended aims of translating interventions into implementations in the country. These valuable skills are also transferred to the management of other institutional responsibilities in environmental governance and beyond. Similarly, the uptake of the Clean Development Mechanism (CDM) was for the benefit of not only project developers and investors, but also for the project-hosting communities by enabling the development of certain community projects. Further, the participation of the UNFCCC in projects is perceived by investors and financiers as a signal that the projects are viable and sustainable (PDs interviews 2019, see also Mawdsley 2018). Such altruistic values placed on the project further help in crowding-in investments from both public and private sector investors (PDs & DFIs interviews 2019).

The growing importance of finance as part of the market logic in climate change governance is evident in the growing and diverse climate financing instruments, including grants from Specialized Funds and carbon trading. Steckel et al. (2016) show that, when properly channeled in line with national socio-economic development priorities, climate financing can become a key pillar in fighting climate change while also driving sustainable development, especially in the Global South (also see Metz and Kok 2008 and Naess et al. 2015). In our analysis of climate financing actions in the Kenyan large-scale renewable energy market, we reveal how financing is strategically leveraged in pre- and post-project completion stages as blended financing, as risk mitigation loans and grants, and as market-incentivizing concessional loans. The result, as the study shows, is improved market efficiency, evident in the increase in public and private sector investments as well as in the deployment of more large-scale renewable energy projects in the country.

Although financialization is not yet observed in the project financing of these large-scale project, because of the dominance of financing from development financial institutions and other public investors as risk-mitigating actors (Klagge and Nweke-Eze 2020), the findings of this study point to the manifestation of financialization rather in financial interventions on the conditions of the market for better efficiency. These financialization processes manifest as private for-profit firms increasingly emerge as intervening consultants, seeking to close the leveraging gaps created due to bureaucratic challenges in leveraging climate financing, for profit. This observed emerging financialization is expected to continue to widen (Knox-Hayes 2010, Johnson 2015, Bracking 2015, 2016, 2019) insofar as more market-based mechanisms continue to apply in the governance of climate change in the country. Observing the emergence of such financialization patterns in climate finance in the future and researching their dynamics, especially in the Global South context, requires more research. This is worthwhile as the use of market-based instruments in climate mitigation and adaptation continues to deepen with the signing of the Paris Agreement.

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