Indigenous Knowledge Aware Drought Monitoring, Forecasting and Prediction using Deep Learning Techniques

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1. Introduction

Drought is a natural environmental hazard causing adverse impacts on vegetation, animals, and people. It can be defined as a deficiency of rainfall or increase of evapotranspiration over a prolonged period of time. In recent years, it has occurred frequently in all climate zones and significantly affecting crop yields and causing a shortage of food as well as animal forage. As stated in [1], drought can be categorized as agricultural, hydrological, meteorological, and socioeconomic droughts. The first three deal with the mechanisms of measuring drought as a physical phenomenon, while the last deals with drought in terms of supply and demand following shortage of rainfall [2]. In Ethiopia, more than 80 percent of people rely on agriculture and livestock for their livelihoods. Most of the population substantially dependent on rain-fed agriculture and the country's economy is extremely vulnerable to the impacts of drought [21]. Thus, among all extreme climate events, drought is considered as the most complex phenomenon affecting the country due to the variable nature of climate condition and the absence of effective technology-oriented climate change early warning systems at the national level. As per the report from the Food and Agriculture Organization of the United Nations (FAO), yet the increasing frequency and magnitude of climate disasters and plant pests over the years have left many communities particularly vulnerable to food insecurity [20]. Consecutive seasons of poor rainfall in southern and southeastern pastoral areas of Ethiopia have severely limited feed and water availability and significant livestock losses have driven rising food insecurity and malnutrition rates, which are largely a consequence of insufficient and underfunded livelihoods response.

Through time, due to the frequent nature of drought in Ethiopia, indigenous peoples and local communities with a long history of interaction with the environment have dealt with climate changes and extreme drought events using indigenous knowledge. As a result, this knowledge can be important plus to develop a system that guides the community by adapting the daily activities of the community itself towards climate mitigation and risk minimization [12, 13]. This can also be considered as the usage of local knowledge with the idea of "*local-solutions for local-problems*". As indicated in the report, "Realizing the Future We Want", the United Nation System Task Team on the Post 2015 UN Development Agenda, acknowledges the importance of indigenous knowledge for environmental sustainability [11] stating that "traditional and indigenous knowledge, adaptation and coping strategies can be major assets for local response strategies". The importance of indigenous peoples' contribution in the adaptation to climate change is also acknowledged in the Assessment Report (AR5) of the Intergovernmental Panel on Climate Change (IPCC), which identifies indigenous and traditional knowledge as a "major resource for adapting to climate change". Studies carried out so far also stress the importance of indigenous knowledge in the development by talking about the idea of "development from below" [3]. Through their research illustrating the utility of indigenous knowledge, these scholars attempted to raise awareness among policymakers about the importance of bottom-up perspectives to create a more locally appropriate and environmentally sustainable solutions. This is also an issue that was re-affirmed in the International Indigenous Peoples' Forum on Climate Change (IIPFCC). Besides this recognition, very little attention has been given by machine learning experts in order to integrate indigenous knowledge for climate change mitigation strategies.

In this natural hazard, significant hydrological components such as storm, rainfall, stream flow, soil moisture, and evaporation are substantially random in their behavior, accordingly, climate change experts try to quantify it using probability, statistics, and at-large stochastic approaches oriented tools. Nowadays, development of drought monitoring, forecasting and prediction system have been achieved in many continents and countries [4]. For instance, in United States [5], a drought monitoring system which has a goal of tracking and displaying the magnitude and spatial extent of drought and its impacts across the States is already modelled and classifies drought into five classes named as moderate, severe, extreme, exceptional, and abnormal drought using six drought indicators. Moreover, other researchers have also conducted drought monitoring for other continents [6, 7, 8, 9]. However, due to, variable characteristics of drought from region to region [10, 16], limited dataset size, limited consideration of valuable local knowledge related to climate change mitigations and block-box nature of current model development and implementation of regional and country-level monitoring and prediction models is very crucial for drought monitoring.

Therefore, in order to cope with drought at an early stage and minimize its impacts, transfer learning based indigenous knowledge-aware drought modeling and prediction using deep learning techniques is a solution that creates an intelligent model for drought monitoring, forecasting and prediction. So that, different concerned bodies and stakeholders can respond to drought occurrences in a better and more precise manner using locally grounded technological solution that takes into account the localized nature of this phenomenon. This way of modelling will also be used in preserving indigenous knowledge and sharing drought features at training and prediction of explainable drought monitoring artificial intelligent systems from reasonable size of data set.

2. Motivation and Statement of the Problem

Issue of drought is great agenda for both developed and developing countries and its impact is higher when it occurs in developing countries like Ethiopia due to the fact that the majority of the population depend on rain-fed agriculture using the traditional way of farming. Yet while there is a growing interest in modeling drought monitoring and prediction; designing a locally grounded, accurate drought modelling and prediction model for agriculture dependent countries requires special considerations with integration of indigenous knowledge and modern scientific methods, so that the people-centered drought modelling and prediction can empower people at the local level by increasing their sense of ownership on technological advancements on climate change mitigation. As also stated in [15], indigenous knowledge could be used, in combination with scientific knowledge, in the co-production of new knowledge useful to orient more locally grounded adaptation and mitigation strategies. Thus, by considering this beneficial usage of indigenous knowledge and benefits of drought modelling and drought impact minimization lagging behind in Ethiopia, "*Indigenous Knowledge and Deep Learning for Climate Change*" has to be used as a flag towards performing an intelligent task on behalf of human beings (drought experts) related to drought monitoring and prediction with the integration of local knowledge in a way that solves large dataset requirement and black box nature of current modelling with integration of certain and structured indigenous knowledge graph (ontology). Moreover, the random and nonlinear nature of drought variables also makes accurate drought predictions remain a challenging scientific problem. Therefore, while current globally motivated drought models can help to predict changes in long-term trends, the accuracy of these models also needs to be improved and at the same time, it has to be localized by considering the local behavior of the drought.

3. Objective

The general objective of this proposed research work is to design deep learning based hybrid comprehensive framework for drought monitoring, forecasting and prediction using scientific and indigenous knowledge of drought. In order to realize the stated general objective, the following specific objectives are identified:

- To assess drought monitoring, forecasting and prediction techniques and approaches;
- To define the requirements for drought monitoring, forecasting and prediction;
- To model indigenous knowledge-driven knowledge base of drought;
- To select an appropriate approach, techniques, and tools for drought monitoring, forecasting and prediction;
- To propose a comprehensive architecture for drought monitoring, forecasting and prediction model;
- To develop and evaluate hybrid drought monitoring, forecasting and prediction model.

4. Methods

For the purpose of this work, design science research methodology [18] will be adopted, it consists of six steps: problem identification and motivation, objectives of the solution, design and development, demonstration, evaluation and communication. The primary data of this research will be collected through questionnaires, interviews and opinionnaires while the secondary data will be collected from the meteorological station of the government, online satellite imagery, spatial data provider, reliable online data providers and other online climate datasets. In order to gather drought-related data, purposive or expert sampling will be used in which samples are expressly chosen in the light of available information by maximizing relevant representation based on prior knowledge from different climate change stakeholders in Ethiopia. The controls in such samples are usually identified as representative areas, representative characteristics of individuals, or types of groups (farmer, pastoralist, environmental-expert etc.). Besides, this sampling is also used for the selection of geographical area and villages under the study site (i.e., Ethiopia). Deep learning based drought modeling with knowledge base integration will be used as a method of modeling [18, 19, 24] following the neural networks that have shown great promise over the last two decades in modeling nonlinear time series because deep learning uses multilayer processing that provides better accuracy as in resemblance with state-of-the-art algorithm as indicated in Figure 1. In addition to this, information about hydrologic processes and behaviors between basins, time and unobserved locations will also be transferred using the neural network techniques for time series and adoption the recent excitement of deep neural networks and transfer learning

[23] is promising to uncover relationships in nonlinear data of drought modeling. Planet's Python Client, Rasterio, Sentinelsat, Geopandas, and ARCGIS will be used for satellite image analysis and processing. Python programming language will be used to develop the model and as a machine learning tool, keras gpu version with tensor-flow backend will be used following the recent ease model development through better computational capabilities.

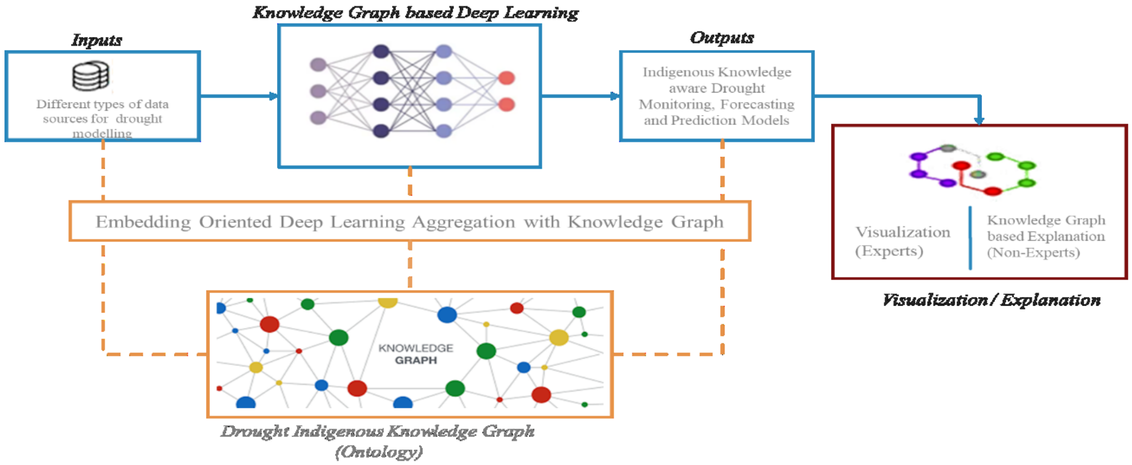

Figure 1: *Comprehensive Architecture of Indigenous Knowledge aware Drought Monitoring Forecasting and Prediction using Deep Learning Techniques*

5. Study Site

Ethiopia is located in the Horn of Africa within 3–15°N and 33–48°E, it is the study site of this proposed research work. Ethiopia is selected as the case study catchment because the reiterated and extreme weather events pose challenges to the main agricultural sector of the country. Thus, studying Ethiopic perspective of drought monitoring and prediction in line with the continental and global climate change is vital for sustainable development. As a result, continental and global drought prediction data for model generalization and transfer learning will also be used from different data sources, including: Ethiopian Meteorological Agency, Climate Research Unit (CRU) Rainfall Data, Early Warning and Response Directorate (EWRD), Data for Sustainable Development Goals (www.data4sdgs.org), Satellite and Weather Data (www.tuhoma.org), Ethiopian Space Science and Technology Institute (ESSTI), GIDMaPS, African Flood and Drought Monitoring Archive and Sentinel Satellite Image (https://scihub.copernicus.eu/dhus/).

6. Expected Outputs and Beneficiaries

Successful completion of this research provides drought prediction and monitoring model that creates a platform for drought-related decision making with different expected outcomes, including drought-driven indigenous knowledge model that has to be integrated with a scientific model for drought monitoring, prediction and mitigation best practices [17, 18]. Drought risk identification model, drought monitoring model, drought preparedness model, drought forecasting model, drought mitigation model and post drought best practices recommendation model are expected outputs of this research work by integrating indigenous and scientific knowledge. As stated in [22], approximately three million Ethiopians are affected by crop production shortfalls adding to the 7.6 million supported every year by the Productive Safety Net Program for some of Ethiopia's poorest and most food-insecure families because of extreme drought and the outputs of this work has direct benefits of reducing this loss. Thus, the expected outputs of this work shall minimize the high impact of weather events related to drought [16] by having state of the art transfer learning based indigenous knowledge aware drought monitoring and prediction system for more than 10 million populations in Ethiopia. As a result, the short and long-term beneficiaries of this proposed work are: the government and its various agriculture and weather-related sectors by improving their drought-related preparedness to increase resilience to drought impacts; citizens and the general public by reducing famine risks and ensures continuity of economic activities to the extent possible during drought periods; and policymakers by having evidence of drought and other interrelated concerns in policy-making.

7. Conclusion

To summarize, this proposed research work integrates connectionist and symbolic artificial intelligence in order to create locally grounded comprehensive, explainable intelligent model for drought monitoring forecasting and prediction. Therefore, using this approach it is possible to create an improved and explainable model from reasonable size dataset with integration of structured indigenous knowledge.

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