Research Proposal

Applications of Machine Learning methods in exploring the implication of Climate change on Global Food Security

Yashvini Shukla

yashvini.shukla.17@ucl.ac.uk

Abstract (200 words)

With the increased effects of climate change becoming more apparent worldwide, the latest research in the scientific community seems to be pessimistic in humans managing to keep warming under 2˚C. We must identify the components of society it is most likely to affect and how the apparent subsequent non-linear effects may precipitate these harms which society has so far failed to mitigate. One critical concern in current food security models is the sub optimal attention paid to 'tipping points' in the earth's climate system, or events that could trigger warming feedback loops. Food security is a big part of global stability, and recent studies have shown that telekinetic events threatening the stable crops of maize, rice, wheat in the major food baskets of the world. By investigating the underpinnings of many climate models in literature and studying their weak points, the Big Data deluge in Spatio-Temporal Analysis from satellite data could be used as an opportunity to use Machine learning and other forms of artificial intelligence to make better predictions of crop yields/ failure risk. This can help inform policymakers to implement appropriate strategies to effectively transition to more reliable food provision systems such as aquaponics and vertical farms and implement principles of Climate Smart Agriculture to improve adaptation and resilience of communities.

1 Introduction

Food insecurity is an exigent problem affecting millions of people round the world as the threat of climate change increases the risk of the world's main food baskets failing simultaneously. (Gaupp et al., 2019) With the Arab Spring linked to the rise in prices of wheat due to failed crop in Russia, one of the main exporters of wheat worldwide, food scarcity has been linked to widescale conflict, generational trauma, malnutrition and death. (Mehrabi, 2020) In the 2011 drought in the Africa, 143,000 -273,000 deaths were linked to famine in Somalia (Checchi, et al, 2013) alone, with the 2019 draughts in the United Kingdom (UK) leading to heat stress and crop failure.
Predicting global patterns of long-term food security threats arising from climate change using machine learning techniques can have enormous impact in informing policy of governments in both developing and developed countries. (Javier and Hausner, 2020)

Significance:

A new Lloyds London report claims that there could be mass global instability in the coming years from climate change induced food insecurity throughout the world. (Lloyds.com, 2015) The Food and Agricultural Organisation (FAO) found out that over 5 per cent of the population in 79 developing countries were undernourished in 2015. The significance that this research would have in informing decision makers to make better decisions and potentially mitigate, prepare for social unrest/ enable future contingencies makes it an interesting topic to pursue. Additionally, the implication that thawing permafrost in Siberia has on the feedback loops is a lesser studied area that needs more attention and collaboration between researchers of different fields, and as a Civil engineer, I think the problem-solving skills and practical world application skills that I have developed are essential in forming the debate about mitigation strategies for inevitable climate driven problems.

Interest: Climate tipping points linked to increased fire risk in Arctic Peatlands

From the desk study of the various research material available in food scarcity, the possibility of the models not being accurate and the possibility of the earth's ecosystem already moving to tipping points of Arctic peatlands made me interested in the reasons behind the global collapse (Steffen et al., 2018). Understanding the rapidly evolving conditions in the Arctic would help to understand in detail the consequences and improve the models, things that are less understood in general and predict with machine learning the likely bringing scenarios of the 'methane dragon ' that could create effective conditions for a hothouse earth. There are worrying signs of this already happening (Carrington, 2019), which increases the exigency of the need to do effective studies as it happens to capture essential signals vital in warning against extreme climate events and help in effective climatic disaster management that may not be averted through mitigation/new technology/ policy level intervention.

Drought forecasts for food security modelling

Improving current climate models, by accounting for thawing peat, and increasingly greener Arctic areas that could worsen the already occurring positive global heating feedback loops would be an interesting problem to solve. It is imperative to the global community to understand in detail the threat presents to global food security and consequently international law, migration, human rights, security, etc. (Food system Shock, 2015) Preliminary literature review shows a lot of insights into the global food security system however future predictions of climate change, water scarcity and population pressure show that it is imperative to model this effect in lieu of feedback loops not accounted/ sparsely accounted for before. However, due to the width of the topic and concern, more detailed review and exploration of available data sets will be needed, possibly obtained in collaboration with the Met Office and the MOSAiC (Multidisciplinary drifting Observatory for the Study of Arctic Climate) expedition to the Arctic. This expedition has researchers withing UCL (Prof. Michel Tsamados, whom I had a chance to contact) where it will be easy to collaborate with them and understand the unprecedented changes since the last ice age happening to the Arctic currently. (Henson, 2020)

2 Literature Review

- **Current research**

There has been a renewed interest in the global food due to the realisation that animal agriculture and food waste is one of the biggest drivers of Anthropogenic climate change, with 34% of ice-free land in the world being dedicated to food production. (Ramankutty et al, 2008) There is a massive waste of resources as third of the food made never gets eaten, which could potentially save 87 Gigatons of carbon sequestered. There are many researchers therefore working on food security, from the reduction of inefficiencies from the production, storage, distribution and subsequently consumption.(Sharma et al., 2020)

On the production side, climate change has increased the likelihood of extreme temperatures over more than 80% of observed global land areas, with an estimated 7% probability of simultaneous losses across the world’s maize breadbaskets with warming of 2°C, and 86% with 4°C warming. (Mehrabi, 2019) Machine learning can help in modelling those parts of the weather system that directly affect the crop yields, like in Bangladesh, India, and Africa where the crop yields of various stables are forecasted using models using ML to predict the data.

Using machine learning to model the climate and the increased temperature models, for instance, is useful because of the many hidden variables that follow non linear characteristics that affect the weather and therefore crop yields. On a meta level, there are two systematic literature reviews (SLR) found, which studied the main focus areas of the climate modelling problems. Most work in the field of using machine learning in drought and predicting the weather is relatively new, and centred on historic data sets that have not been updated (Huntingford et al., 2019). Precipitation has a positive correlation with food yields in India and China (Chen et al., 2020) and the weather can be considered a direct proxy for food security, like in Bangladesh. Many weather effects like El Nino that have been well studied because of the economic impact they have on the lives of billions of people, and factors such as green cover, soil type have been used to predict up to a 90% accuracy level the effectiveness of machine learning models in Bangladesh (Jakariya et al., 2020).

There are potential applications in using Machine learning to understand runaway climate change as teleconnections between the various meta models of different climates in the world could benefit from the ability of ML algorithms to discover hidden variables (unknown unknowns) too. (Huntingford et al., 2019)

3 Current state of the art

Climate system models, Wildfire risk modelling are one of the most complex fields involving vast amounts of latent variables involved in modelling such a complex phenomenon. Research suggests that Earth System Model (ESM) diagnostics is an effective model in conjunction with the relatively new machine learning field to put to use the vast amounts of data gathered daily over satellites and other earth monitoring systems. To model weather patterns like rainfall, researchers have attempted to use Artificial Neural Networks (ANNs) and modify the parameters of climate events, like El Niño-Southern Oscillation (ENSO) which has great economic significance over South Asian subcontinent (Shukla et al., 2011). In an unrelated study, researchers found out that Extreme Learning Machine (ELM) predicted monthly Effective Drought Indices in cornfields in Australia, (which have a direct relationship with food supply) more accurately than ANN models. (Deo and Şahin, 2015)

Drought forecasts - Machine learning models have also been applied to Bangladesh , where there was an assessment of climate induced agricultural vulnerable coastal communities of Bangladesh (Jakariya et al., 2020) A model used in the US to predict draught factors found a strong fit of a Random Forest regression method applied compared to other two Machine Learning (ML) methods which shows that potential that with even remote sensing data is available even with limited in situ data availability, with suggestions to study draught separately brought about by meteorological and hydrological conditions. (Park et al., 2016) A 2019 study of the rice yields under climate change in Sahel, Burkina Faso shows that ANNs are effective in testing predictions against observations, and when extrapolated to the year 2052, show a staggering 57.29% gap in recorded maximum yields (Zhang et al., 2019). However a significant limitation of this study is that is conducted on the RCP (Representative Concentration Pathways) emissions scenario by the IPCC (International Panel on Climate Change) where significant knowledge gaps of the nonlinearities, nascency and uncertainty of scientific literature is jeopardizing accurate modelling of temperatures which is a crucial need when modelling crop yields. (Ipcc.ch, 2015)

On a different note, a study have shown that the nutritional component of rice could also change with climate change, not directly related to crop yield, but indirectly from heat stress affecting nutrient uptake in plants that could subsequently cause deficiencies in 600 million people. (Zhu et al., 2018)

4 Shortcomings

A comprehensive literature review of over 567 relevant studies from 6 electronic data bases concluded that the most used parameters for modelling crop yields are temperature, rainfall and soil type, and most applied algorithm is that of a Convulational Neural Network (CNN), Long-Short Term Memory (LSTM) and Deep Neural Networks (DNN) (van Klompenburg, Kassahun and Catal, 2020)

The scientific community is in deep concern from the fact that the Arctic permafrost has begun to thaw earlier than most climate models predicted, (Maslin and Austin, 2012) and creating for the first time in recent geological history wildfires that could trigger positive feedback loops of greenhouse gas emissions and warming in an ecologically fragile area of the Arctic. Due to the Arctic island effect (the pole heating faster than the rest of the world) the Arctic is in dire need of reassessment of the assumptions behind the models that did drought predictions that will not be able to accurately account for sudden catastrophic events. (Valdes, 2011).

Since Anthropogenic climate change will affect the agricultural sector more directly than any other because of its direct dependence on weather (Porter et al 2013), most predictions about agriculture outside the realm of advancement in technologies is limited by the accuracy of the climate prediction models. However machine learning models tend to give different results than traditionally statistical methods in the realm of climate modelling. (Crane-Droesch, 2018) This means a lot of previous studies done in food security need updated conditions of the model they use to make the food security predictions, taking into account non linearities and changes in the climate because of tipping points. Additionally, the call for papers by the Journal of Agricultural Forest Meterology in its special issue of Advances in Remote Sensing for Crop Yield Estimation (Elsevier.com, 2020) for the period till 2021 shows that there is persistent interest in the field of remote monitoring of satellite big data in order to better estimate crop yields. In the face of climate change, where machine learning methods as further studied and suggested by the global community of climate change and AI enthusiasts suggests expert identification of gaps in the knowledge base that ought to be filled. (Rolnick et al., 2019)

According to a study done in 2020 after analysing topics based on semantic similarity using Natural Language Processing (NLP), there has been found to be strong scientific interest in the tundra that reflects the concern of the rapid warming of the Arctic, the authors recommended a cross disciplinary approach to fully assess the implications of the changes that a warming Arctic has on society (Javier and Hausner, 2020). Therefore there seems to be a need to integrate the latest climate research and changing models with the different tipping points, and in detail explore the ramification on global food security. There also seems to be a gap of research in the studying of the effects of population growth and the effective policies that would be central to substantially decrease greenhouse gases. (Project Drawdown, 2020) The use of machine learning in analysing large scale population and educational health outcomes to target government policy in those areas to reduce resource pressure sound like a useful goal to pursue. Current food basket predictions aren't very quantitative or concrete in giving policy makers a lead in the likelihood of planning for a collapse in food supplies and the exact timings and expectations of when such a thing could happen, and what to do to mitigate its impact can be done through the intersection of demand (population modelling) and supply (climate model and drought prediction).

5 Research Ideas to address shortcomings

Previous studies done in food security need updated conditions of the model they use to make the food security predictions, both for the reasons of a revision of the model given the feedback loops that may have been surpassed due to higher emissions by now as of 2020, and the greater accuracy of Machine Learning models in realising better outcome driven decisions. (Yang, Zhao and Cai, 2020) As computing power increases, many researchers are finding contradictory climate predictions from models, that it has become unsettling not to have a consensus on the model to be used by most researchers applying those models, which needs further investigation in identifying the models and the assumptions behind them. Therefore I would like to understand the Arctic environment better in collaboration with UCL and non-UCL academics in the field and know the implications of the climate tipping points to make accurate predictions on food security.

In terms of impact and scale of the problem of climate change, it seems that investigating the research using machine learning models could help understand the emissions scenarios by taking of 85 gigatons of carbon from the atmosphere for a growing human population. (Project Drawdown, 2020) Many papers do seem to suggest a wide societal and scientific research amnesia regarding modelling the consequences of a growing human population on natural resources, however the most important of which is food, which could also be a possible exploration avenue of my research. (Dodson et al., 2020)

Adaptation to climate change through the choice of cropping system and sowing date in subSaharan Africa was done additionally, would be a valuable outcome of the research in informing public policy to help those regions adapt to the dire conditions. In a comprehensive literature review of 93 research articles in the sustainable agricultural supply chain performance, it has been suggested that future studies could explore the extent of the ML application in different regions of the world and provide a comparative assessment of the existing models accounting for the tipping points in the climate mentioned earlier. (Sharma et al., 2020)

References

Campbell, A.M., Racault, M.-F., Goult, S. and Laurenson, A. (2020). Cholera Risk: A Machine Learning Approach Applied to Essential Climate Variables. International Journal of Environmental Research and Public Health, [online] 17(24), p.9378. Available at: https://www.mdpi.com/1660-4601/17/24/9378#cite [Accessed 18 Dec. 2020].

Carrington, D. (2019). Climate emergency: world 'may have crossed tipping points'. [online] the Guardian. Available at: https://www.theguardian.com/environment/2019/nov/27/climate-emergency-world-may-have-crossed-tipping-points [Accessed 25 Dec. 2020].

Crane-Droesch, A. (2018). Machine learning methods for crop yield prediction and climate change impact assessment in agriculture. Environmental Research Letters, [online] 13(11), p.114003. Available at: https://iopscience.iop.org/article/10.1088/1748-9326/aae159 [Accessed 21 Dec. 2020].

Deisenroth, M. (2010). Faculty of Informatics Institute for Anthropomatics Intelligent Sensor-Actuator-Systems Laboratory (ISAS) Efficient Reinforcement Learning using Gaussian Processes. [online] Available at: https://smlgroup.cc/pdf/thesis.pdf [Accessed 24 Dec. 2020].

Deo, R.C. and Şahin, M. (2015). Application of the extreme learning machine algorithm for the prediction of monthly Effective Drought Index in eastern Australia. Atmospheric Research, [online] 153, pp.512–525. Available at: https://www.sciencedirect.com/science/article/pii/S0169809514003858?via=ihub#bb0320 [Accessed 18 Dec. 2020].

Dodson, J.C., Dérer, P., Cafaro, P. and Götmark, F. (2020). Population growth and climate change: Addressing the overlooked threat multiplier. Science of The Total Environment, [online] 748, p.141346. Available at: https://www.sciencedirect.com/science/article/pii/S0048969720348750?casa_token=nDRsOyPjkCYAAAAA:IrDs8tYEGsdRcGrsBksgUCG0z12HAN10RKPIbYqA1rmdicsawPAXcHq1EMCrKM1wAa7ObFAY#bb0345 [Accessed 21 Dec. 2020].

Elsevier.com. (2020). Agricultural and Forest Meteorology. [online] Available at: https://www.journals.elsevier.com/agricultural-and-forest-meteorology/call-for-papers/advances-in-remote-sensing-forcrop-yield-estimation [Accessed 24 Dec. 2020].

Food system shock: The insurance impacts of acute disruption to global food supply - Lloyd's - The world's specialist insurance market. Also known as Lloyd's of London; is a market where members join together as syndicates to insure risks. [online] Available at: https://www.lloyds.com/news-and-risk-insight/risk-reports/library/society-andsecurity/food-system-shock [Accessed 18 Dec. 2020].

Gaupp, F., Hall, J., Hochrainer-Stigler, S. and Dadson, S. (2019). Changing risks of simultaneous global breadbasket failure. Nature Climate Change, [online] 10(1), pp.54–57. Available at: https://www.nature.com/articles/s41558-0190600-z#further-reading [Accessed 23 Dec. 2020].

Henson, B. (2020). NOAA report card: Arctic is having more and more warming difficulties » Yale Climate Connections. [online] Yale Climate Connections. Available at: https://yaleclimateconnections.org/2020/12/noaa-reportcard-Arctic-is-having-more-and-more-difficulties/ [Accessed 24 Dec. 2020].

Huntingford, C., Jeffers, E.S., Bonsall, M.B., Christensen, H.M., Lees, T. and Yang, H. (2019). Machine learning and artificial intelligence to aid climate change research and preparedness. Environmental Research Letters, [online] 14(12), p.124007. Available at: https://iopscience.iop.org/article/10.1088/1748-9326/ab4e55 [Accessed 22 Dec. 2020].

Huntingford, C., Jeffers, E.S., Bonsall, M.B., Christensen, H.M., Lees, T. and Yang, H. (2019). Machine learning and artificial intelligence to aid climate change research and preparedness. Environmental Research Letters, [online] 14(12), p.124007. Available at: https://iopscience.iop.org/article/10.1088/1748-9326/ab4e55 [Accessed 28 Dec. 2020].
Ipcc.ch. (2015). Chapter 3 — Global Warming of 1.5 oC. [online] Available at: https://www.ipcc.ch/sr15/chapter/chapter-3/ [Accessed 24 Dec. 2020].

Jakariya, Md., Alam, Md.S., Rahman, Md.A., Ahmed, S., Elahi, M.M.L., Khan, A.M.S., Saad, S., Tamim, H.M., Ishtiak, T., Sayem, S.M., Ali, M.S. and Akter, D. (2020). Assessing climate-induced agricultural vulnerable coastal communities of Bangladesh using machine learning techniques. Science of The Total Environment

Javier, F. and Hausner, V.H. (2020). Research gaps and trends in the Arctic tundra: a topic-modelling approach. Munin.uit.no. [online] Available at: https://munin.uit.no/handle/10037/19505 [Accessed 28 Dec. 2020].

Lenton, T.M., Held, H., Kriegler, E., Hall, J.W., Lucht, W., Rahmstorf, S. and Schellnhuber, H.J. (2008). Tipping elements in the Earth's climate system. Proceedings of the National Academy of Sciences, [online] 105(6), pp.1786–1793. Available at: https://www.pnas.org/content/105/6/1786 [Accessed 22 Dec. 2020].

Mansfield, L.A., Nowack, P.J., Kasoar, M., Everitt, R.G., Collins, W.J. and Voulgarakis, A. (2020). Predicting global patterns of long-term climate change from short-term simulations using machine learning. npj Climate and Atmospheric Science, [online] 3(1). Available at: https://www.nature.com/articles/s41612-020-00148-5 [Accessed 15 Dec. 2020].

Maslin, M. and Austin, P. (2012). Climate models at their limit? Nature, [online] 486(7402), pp.183–184. Available at: https://www.nature.com/articles/486183a [Accessed 19 Dec. 2020].

McGovern, A., Elmore, K.L., Gagne, D.J., Haupt, S.E., Karstens, C.D., Lagerquist, R., Smith, T. and Williams, J.K. (2017). Using Artificial Intelligence to Improve Real-Time Decision-Making for High-Impact Weather. Bulletin of the American Meteorological Society, [online] 98(10), pp.2073–2090. Available at: https://journals.ametsoc.org/view/journals/bams/98/10/bams-d-16-0123.1.xml [Accessed 22 Dec. 2020].

Mehrabi, Z. (2019). Food system collapse. Nature Climate Change, [online] 10(1), pp.16–17. Available at: https://www.nature.com/articles/s41558-019-0643-1 [Accessed 23 Dec. 2020].

Mishra, A.K. and Desai, V.R. (2006). Drought forecasting using feed-forward recursive neural network. Ecological Modelling, [online] 198(1–2), pp.127–138. Available at: https://www.sciencedirect.com/science/article/pii/S0304380006002055?via%3Dihub [Accessed 22 Dec. 2020].

Park, S., Im, J., Jang, E. and Rhee, J. (2016). Drought assessment and monitoring through blending of multi-sensor indices using machine learning approaches for different climate regions. Agricultural and Forest Meteorology, [online] 216, pp.157–169. Available at: https://www.sciencedirect.com/science/article/pii/S0168192315007467 [Accessed 24 Dec. 2020].

Project Drawdown. (2020). Table of Solutions | Project Drawdown. [online] Available at: https://www.drawdown.org/solutions/table-of-solutions [Accessed 28 Dec. 2020].

Rolnick, D., Donti, P., Kaack, L., Kochanski, K., Lacoste, A., Sankaran, K., Ross, A., Milojevic-Dupont, N., Jaques, N., Waldman-Brown, A., Luccioni, A., Maharaj, T., Sherwin, E., Mukkavilli, S., Kording, K., Gomes, C., Ng, A., Hassabis, D., Platt, J., Creutzig, F., Chayes, J. and Bengio, Y. (2019). Tackling Climate Change with Machine Learning. [online] Available at: https://arxiv.org/pdf/1906.05433.pdf.

Saemundsson, S., Hofmann, K. and Deisenroth, M. (n.d.). Meta Reinforcement Learning with Latent Variable Gaussian Processes. [online] Available at: https://arxiv.org/pdf/1803.07551.pdf [Accessed 24 Dec. 2020].

Schellens, M.K. and Belyazid, S. (2020). Revisiting the Contested Role of Natural Resources in Violent Conflict Risk through Machine Learning. Sustainability, [online] 12(16), p.6574. Available at: https://www.mdpi.com/20711050/12/16/6574 [Accessed 17 Dec. 2020].

Sharma, R., Kamble, S.S., Gunasekaran, A., Kumar, V. and Kumar, A. (2020). A systematic literature review on machine learning applications for sustainable agriculture supply chain performance. Computers & Operations Research, [online] 119, p.104926. Available at:

https://reader.elsevier.com/reader/sd/pii/S0305054820300435?token=682F05449B08B75D9C323A7B642C15B4BB4DF3FB6C4369FE68655F5BFD1069ADB4DD9767C39BD4AAB2165D34EECE6123 [Accessed 24 Dec. 2020].
Shukla, R.P., Tripathi, K.C., Pandey, A.C. and Das, I.M.L. (2011). Prediction of Indian summer monsoon rainfall using Niño indices: A neural network approach. Atmospheric Research, [online] 102(1–2), pp.99–109. Available at: https://www.sciencedirect.com/science/article/pii/S0169809511001918 [Accessed 18 Dec. 2020].

Steffen, W., Rockström, J., Richardson, K., Lenton, T.M., Folke, C., Liverman, D., Summerhayes, C.P., Barnosky, A.D., Cornell, S.E., Crucifix, M., Donges, J.F., Fetzer, I., Lade, S.J., Scheffer, M., Winkelmann, R. and Schellnhuber, H.J. (2018). Trajectories of the Earth System in the Anthropocene. Proceedings of the National Academy of Sciences, [online] 115(33), pp.8252–8259. Available at: https://www.pnas.org/content/115/33/8252 [Accessed 25 Dec. 2020].

Survival. (2011). Global Warming and the Arab Spring. [online] Available at: https://www.tandfonline.com/doi/full/10.1080/00396338.2011.571006 [Accessed 23 Dec. 2020].

Valdes, P. (2011). Built for stability. Nature Geoscience, [online] 4(7), pp.414–416. Available at: https://www.nature.com/articles/ngeo1200 [Accessed 18 Dec. 2020].

Van Klompenburg, T., Kassahun, A. and Catal, C. (2020). Crop yield prediction using machine learning: A systematic literature review. Computers and Electronics in Agriculture, [online] 177, p.105709. Available at: https://www.sciencedirect.com/science/article/pii/S0168169920302301 [Accessed 24 Dec. 2020].

Yang, P., Zhao, Q. and Cai, X. (2020). Machine learning based estimation of land productivity in the contiguous US using biophysical predictors. Environmental Research Letters, [online] 15(7), p.074013. Available at: https://iopscience.iop.org/article/10.1088/1748-9326/ab865f [Accessed 21 Dec. 2020].

Zhang, L., Traore, S., Ge, J., Li, Y., Wang, S., Zhu, G., Cui, Y. and Fipps, G. (2019). Using boosted tree regression and artificial neural networks to forecast upland rice yield under climate change in Sahel. Computers and Electronics in Agriculture, [online] 166, p.105031. Available at: https://www.sciencedirect.com/science/article/pii/S0168169919312864 [Accessed 24 Dec. 2020].

Zhu, C., Kobayashi, K., Loladze, I., Zhu, J., Jiang, Q., Xu, X., Liu, G., Seneweera, S., Ebi, K.L., Drewnowski, A., Fukagawa, N.K. and Ziska, L.H. (2018). Carbon dioxide (CO2) levels this century will alter the protein, micronutrients, and vitamin content of rice grains with potential health consequences for the poorest rice-dependent countries. Science Advances, [online] 4(5), p.eaaq1012. Available at: https://advances.sciencemag.org/content/4/5/eaaq1012 [Accessed 24 Dec. 2020].