On pseudo-absence generation and machine learning for locust breeding ground prediction in Africa

Ibrahim Salihu Yusuf
InstaDeep

Kale-ab Tessera
InstaDeep

Thomas Tumiel
InstaDeep

Zohra Slim
InstaDeep

Amine Kerkeni
InstaDeep

Sella Nevo
Google Research

Arnu Pretorius
InstaDeep

Abstract

Desert locust outbreaks threaten the food security of a large part of Africa and have affected the livelihoods of millions of people over the years. Furthermore, these outbreaks could potentially become more severe and frequent as a result of global climate change. Machine learning (ML) has been demonstrated as an effective approach to locust distribution modelling which could assist in early warning. However, ML requires a significant amount of labelled data to train. Most publicly available labelled data on locusts are presence-only data, where only the sightings of locusts being present at a particular location are recorded. Therefore, prior work using ML have resorted to pseudo-absence generation methods as a way to circumvent this issue and build balanced datasets for training. The most commonly used approach is to randomly sample points in a region of interest while ensuring these sampled pseudo-absence points are at least a specific distance away from true presence points. In this paper, we compare this random sampling approach to more advanced pseudo-absence generation methods, such as environmental profiling and optimal background extent limitation, specifically for predicting desert locust breeding grounds in Africa. Interestingly, we find that for the algorithms we tested, namely logistic regression, gradient boosting, random forests and MaxEnt, all popular in prior work, the linear logistic model performed significantly better than the more sophisticated ensemble methods, both in terms of prediction accuracy and F1 score. Although background extent limitation combined with random sampling seemed to boost performance for ensemble methods, no statistically significant differences were detected between the pseudo-absence generation methods used to train the logistic model. In light of this, we conclude that simpler approaches such as random sampling for pseudo-absence generation combined with linear classifiers such as logistic regression are sensible and effective for predicting locust breeding grounds across Africa.

1 Introduction

Climatic conditions leading to cyclones and monsoons, causing heavy rains, prompted the recent 2019-2021 upsurge in desert locusts (FAO, 2021a). These upsurges pose a significant threat to food security in affected areas, especially in the Northern parts of the African continent. Furthermore, the occurrence and severity of such upsurges could potentially be exacerbated by global climate change (Vallebona et al., 2008; FAO, 2016; Zhang et al., 2019; Salih et al., 2020).

*Correspondence: i.yusuf@instadeep.com
Data preprocessing and modelling code: https://github.com/instadeepai/locust-predict

Machine Learning for the Developing World (ML4D) workshop, NeurIPS 2021, Sydney, Australia.
The Food and Agriculture Organization (FAO) of the United Nations operate a sophisticated monitoring and early warning system for locust outbreaks (FAO, 2020). The system relies on a range of technologies serving field survey operators, control centres and researchers (Cressman, 2008). In particular, remote sensing has become an invaluable component for early warning because of its usefulness in locust distribution modelling (Latchininsky and Sivanpillai, 2010; Cressman, 2013; Latchininsky, 2013; Klein et al., 2021). Female locusts typically lay their eggs in wet, warm soil and wingless nymph locusts, referred to as hoppers, require specific vegetation nearby to sustain them before their wings develop (Symmons and Cressman, 2001; FAO, 2021b). This connection between certain environmental variables and locust behaviour makes it possible to attempt to model locust distribution through remote sensing combined with survey data (Piou et al., 2013; Escorihuela et al., 2018; Piou et al., 2019; Chen et al., 2020; Ellenburg et al., 2021).

Machine learning (ML) has been shown to be a valuable tool for species distribution modeling (Beery et al., 2021). In particular, many recent papers have looked at using ML specifically for modelling locusts (Gómez et al., 2018, 2019; Kimathi et al., 2020; Gómez et al., 2020, 2021). However, even when remote sensing is capable of providing useful features for such models, ML still heavily relies on large amounts of labelled data for training. Currently, the FAO provides many years worth of labelled data on locusts hosted through their Locust Hub. This is an extremely useful resource and contains recorded sightings of locusts in various phases and stages of their lifecycle. That said, survey teams in general only record the presence of locusts and rarely their absence. This is typical of many ecological surveys and data of this kind are referred to as presence-only data. To overcome the lack of negative labels when training ML models, past work have made use of pseudo-absence generation (Gómez et al., 2018, 2020, 2021). A commonly used approach is to randomly sample points in a region of interest while ensuring that pseudo-absence points are sampled a minimum distance away from any true presence points (Barbet-Massin et al., 2012). More advanced pseudo-absence generation methods also exist, such as environmental profiling and background extent limitation techniques (Iturbide et al., 2015).

In this paper, we compare different pseudo-absence generation methods used in conjunction with ML, including methods such as random sampling, environmental profiling and background extent limitation, specifically when modelling the desert locust species in Africa. We focus on ML algorithms commonly used in prior work: logistic regression (LR), gradient boosting (XGBoost), random forests (RF) and maximum entropy (MaxEnt – a presence-background modelling approach). We train each algorithm on specific environmental variables combined with presence labels from the FAO’s Locust Hub. For LR, XGBoost and RF we generate pseudo-absence labels using each of the above-mentioned pseudo-absence generation methods. Our results show LR performing significantly better in terms of prediction accuracy and F1 score compared to the ensemble methods XGBoost and RF as well as MaxEnt. For LR training, there are no statistically significant differences between the pseudo-absence generation methods, whereas for the ensemble methods, random sampling combined with background extent limitation significantly improved performance. We therefore conclude, as well as simultaneously validate, the approach of random sampling for pseudo-absence generation, used and studied by Gómez et al. (2018, 2019) and Barbet-Massin et al. (2012) to be effective. However, in contrast to these works, we find the simpler linear model LR, as opposed to the RF, to be more suitable when used for breeding ground prediction over a large region of Africa.

2 Methodology

We are interested in testing the effectiveness of different pseudo-absence generation methods combined with ML for modelling locusts. Here we discuss our methodology concerning our data, including our choice of environmental variables and preprocessing. We explain the different pseudo-absence generation methods and ML algorithms in more detail and formally state our research hypothesis.

Data. We focus on modelling desert locusts over the entire affected region of the African continent (we provide the full list of countries in the supplementary material (SM)). We use the FAO’s Locust Hub.

3https://locust-hub-hq.fao.org.hub.arcgis.com/

Presence-background approaches make use of only labelled presence data and points sampled across the entire study area of interest, referred to as background data, without using any absence or pseudo-absence data. Even though MaxEnt does not rely on pseudo-absence generation, we include it in this work as a strong baseline for comparison.
Hub observation data in this study, as it contains the geo-locations of areas where locusts were observed, type of locust observed and some environmental conditions. It has a temporal range of 1985 to 2021. The observations were enriched with environmental data from NASA and ISRIC SoilGrids respectively (names and descriptions of each variable are provided in SM). Our variables include soil characteristics such as moisture, profile (type) and temperature as well as air pressure, humidity and surface level temperature. The environmental data from NASA have a temporal range of 2000 to 2021, while the soil profile information is non-temporal. The three datasets were combined by selecting a region of temporal overlap from 2000 to 2021. As in Gómez et al. (2018), we use hopper presence/absence as a proxy for locust breeding grounds. Given that the maximum time period between the start of egg laying to the end of the hopper phase is approximately 95 days and that hoppers are not able to fly, they remain close to the breeding ground and therefore act as a good proxy. Therefore, we use a 95-day history for all temporal variables and predict hopper presence 7-days into the future as a proxy for predicting the presence of potential future breeding grounds. The resulting dataset was split into train and test sets based on time; the period from 2000-2014 was used for training, while the period from 2015-2021 was used for testing. Pseudo-absence generation was also performed separately on each split ensuring a balanced distribution of hopper presence/absence. After generating pseudo-absences the train set was further split into a smaller train set and a validation set for parameter tuning in the ratio of 80:20. To ensure that different algorithm and pseudo-absence pairs could be tested fairly and on the same test set, we constructed pseudo-absences for the test set by randomly sampling a balanced mixture of test pseudo-absence points generated by the different methods operating on the test set presence points. For more details regarding the dataset, we refer the reader to the SM.

Pseudo-absence generation. We consider four different approaches for pseudo-absence generation detailed in Iturbide et al. (2015) and depicted in Figure 1 (a)-(d):

1. **Random sampling (RS)**: Pseudo-absences are sampled at random across all points in the study area that are not within some minimum selected distance to any presence point. The minimum distance between a presence and any absence point is referred to as the exclusion buffer and is set to 30km for all methods.

2. **Random sampling with environmental profiling (RSEP)**: The RSEP method is aimed at defining the environmental range of the background from which pseudo-absences are sampled. Environmentally unsuitable areas for locusts are defined using a presence-only profiling algorithm (one-class SVM) trained on soil moisture. Once these unsuitable regions have been established, pseudo-absence points are randomly sampled from within them.

---

5https://disc.gsfc.nasa.gov/datasets/GLDAS_NOAH025_3H_2.1/summary
6https://data.isric.org/geonetwork/srv/eng/catalog.search#/home
Figure 2: Pseudo-absence and background data generation: an example on a subset of African countries: Niger, Mauritania, Mali, Algeria, Western Sahara and Morocco for November 2003. (a) Random sampling (RS). (b) Random sampling with environment profiling (RSEP). White regions indicate environmentally suitable regions as identified through environmental profiling, i.e. these are the regions where pseudo-absence points should not be sampled. (c) Random sampling with background extent limitation (RS+). (d) Random sampling with environment profiling and background extent limitation (RSEP+). (e) Background sampling (BS). Note that for BS the red points do not necessarily correspond to absence but could represent both presence and absence.

3. RS with background extent limitation (RS+): Pseudo-absences are sampled at random within a limited background extent not including the full study region. This optimum limited background is determined by a multi-step process as outlined in (Iturbide et al., 2015).³

4. RSEP with background extent limitation (RSEP+): This method is similar to the above RS+, but instead of using unconditioned random sampling within the limited background extent, samples are only within environmentally unsuitable regions identified through profiling.

As a strong baseline we compare these pseudo-absence generation methods to only using presence-background data (see Figure 1 (e)) modeling where background samples are generated over the entire study region of interest without any constraint on their location with respect to presence points.

ML algorithms. We consider the following algorithms for comparison: logistic regression (LR), gradient boosting (XGBoost) (Freund and Schapire, 1997; Friedman, 2001), random forests (RF) (Breiman, 2001) and maximum entropy (MaxEnt) (Phillips et al., 2006). We provide hyperparameter details in SM.

Hypothesis. Our null hypothesis, $H_0$, is that of no difference between the mean performances of the different pseudo-absence generation methods across all the algorithms tested including the mean performance of MaxEnt using only presence-background data. Specifically, let $G = \{rs, rsep, rs+, rsep+\}$, $A = \{lr, xgboost, rf\}$ and let $\mu_g^a$ represent the mean performance for pseudo-absence generation method $g \in G$, used when training algorithm $a \in A$. Then the null hypothesis is given by

$$H_0 : \mu_g^a = \mu_g^{a'} = \mu_{maxEnt}^{BS} \quad \forall g, g' \in G, a, a' \in A | g \neq g' \land a \neq a'$$

(1)

We are required to reject $H_0$ to have evidence that there are indeed differences between the pseudo-absence generation methods used for training the different algorithms as well as the presence-background MaxEnt approach. Our significance level, i.e. the point at which the probability of equal mean performances under the null hypothesis is low enough to reject the null hypothesis, is set to $\alpha = 0.05$. If $H_0$ is rejected, we can continue with more specific pairwise tests, with appropriate $p$-value adjustments to control for the family-wise error (Demšar, 2006).

3 Experiments

As an example of the different generation methods, in Figure 2, we show the pseudo-absence points generated by each method in the countries Niger, Mauritania, Mali, Algeria, Western Sahara and Morocco for November 2003.

Results. The mean accuracy and F1 score over 100 runs for each algorithm and generation method is shown in Table 1. In general, the performances are respectable. However, interestingly, the linear model LR is seen to outperform the more sophisticated ensemble methods, XGBoost and RF, across

³We perform all pseudo-absence generation using the nopa R package (Iturbide et al., 2015).
Table 1: Performance comparison between generation methods and ML algorithms. Bold values indicate top performance across generation methods for a specific algorithm.

|   | LR       | XGBoost  | RF       | MaxEnt   |
|---|----------|----------|----------|----------|
| Accuracy | RS 0.8499 ± 0.0021 | 0.7320 ± 0.0016 | 0.6623 ± 0.0112 | 0.7418 ± 0.0019 |
|        | RSEP 0.8541 ± 0.0020 | 0.7020 ± 0.0015 | 0.6706 ± 0.0133 | 0.7418 ± 0.0019 |
|        | RS+ 0.8417 ± 0.0020 | 0.7580 ± 0.0021 | 0.7855 ± 0.0176 | 0.7418 ± 0.0019 |
|        | RSEP+ 0.8530 ± 0.0022 | 0.7423 ± 0.0021 | 0.7712 ± 0.0138 | 0.7418 ± 0.0019 |
| F1     | RS 0.9064 ± 0.0012 | 0.8157 ± 0.0009 | 0.7495 ± 0.0104 | 0.5437 ± 0.0035 |
|        | RSEP 0.9098 ± 0.0011 | 0.7895 ± 0.0008 | 0.7576 ± 0.0121 | 0.5437 ± 0.0035 |
|        | RS+ 0.9008 ± 0.0011 | 0.8448 ± 0.0012 | 0.8060 ± 0.0121 | 0.5437 ± 0.0035 |
|        | RSEP+ 0.9093 ± 0.0013 | 0.8293 ± 0.0012 | 0.8527 ± 0.0101 | 0.5437 ± 0.0035 |

Figure 3: SHAP analysis for logistic regression. An interpretation of the logistic regression model on the different pseudo-absence generation methods using Shapley additive explanations (Lundberg and Lee, 2017). (a) Random sampling (RS). (b) Random sampling with environment profiling (RSEP).

all generation methods, as well as MaxEnt, both in terms of absolute mean accuracy and F1 score. Next, we ascertain the statistical significance of these results.

Statistical analysis. We test $H_0$ using the Friedman aligned ranks test (Friedman, 1937) and find that we can easily reject the null hypothesis of no difference with $p$-value < $2 \times 10^{-16}$. Having rejected $H_0$, we perform additional pairwise tests using the $p$-value adjustment procedure for multiple testing from Holm (1979). For XGBoost and RF significant differences are detected between the generation methods (all $p$-values < $2 \times 10^{-16}$), providing evidence that background extent limitation can be of benefit to these ensemble methods. For LR, the differences between the generation methods are not significant ($p$-values provided in SM). Given the seemingly absolute superiority in performance from LR with no difference between generation methods, we conduct a pairwise test between only the top performing algorithms and generation pairs and LR using the simplest random sampling. More specifically, we test the null hypothesis $H_0^\mu : \mu_{r+} = \mu_{r+}^{xgb} = \mu_{r+}^{maxent}$. We find that the difference between LR and the other algorithms to be significant ($p < 2 \times 10^{-16}$).

Interpretation. In Figure 3, we provide a SHAP analysis (Lundberg and Lee, 2017) for variable importance of the LR model between using RS or RSEP. We find that only a few of the total 174 features are important for prediction. For both methods features such as $\text{Albedo}_\text{inst}_\text{bucket}_14$ and $\text{clay}_0.5\text{cm}_\text{mean}$ roughly amount to the same predictive effect as the bottom 165 variables combined. This is in contrast to the ensemble methods where feature importance is far more spread out. Therefore, we suspect the LR is performant due to its ability to avoid overfitting to noisy features.

4 Discussion

Our study provides some evidence for the suitability of using random sampling for pseudo-absence and logistic regression for predicting desert locust breeding grounds in Africa. We note that a detailed analysis of pseudo-absence generation appeared in Barbet-Massin et al. (2012), but was performed on synthetic data, whereas we are primarily interested in locust modeling and considered more modern methods such as background extent limitation. Finally, although we find linear models to perform well in our study, recent papers have started to use deep learning for locust modeling (Samil et al., 2020; Tabar et al., 2021), moving towards more sophisticated ML model architectures and leveraging promising new sources of data such as those generated by the eLocust3m app (PlantVillage, 2020) to good effect. We hope to compare with and potentially contribute to these approaches in future work.

We conducted our statistical testing in R using the `stats` library where $2 \times 10^{-16}$ is considered the minimum $p$-value. Values smaller than this are indicated with the ‘<’ symbol in printed output.
Acknowledgments

This research was supported in part through computational resources provided by Google.

References

FAO, “Desert locust upsurge in 2019–2021,” http://www.fao.org/ag/locusts/en/info/2094/web18/index.html, 2021.

C. Vallebona, L. Genesio, A. Crisci, M. Pasqui, A. Di Vecchia, and G. Maracchi, “Large-scale climatic patterns forcing desert locust upsurges in west africa,” Climate Research, vol. 37, no. 1, pp. 35–41, 2008.

FAO, “Weather and desert locusts,” http://www.fao.org/3/i6152en/i6152en.pdf, 2016.

L. Zhang, M. Lecoq, A. Latchininsky, and D. Hunter, “Locust and grasshopper management,” Annual review of entomology, vol. 64, pp. 15–34, 2019.

A. A. Salih, M. Baraibar, K. K. Mwangi, and G. Artan, “Climate change and locust outbreak in east africa,” Nature Climate Change, vol. 10, no. 7, pp. 584–585, 2020.

FAO, “Early warning system,” http://www.fao.org/ag/locusts/en/activ/DLIS/earlywarning/index.html, 2020.

K. Cressman, “The use of new technologies in desert locust early warning,” Outlooks on Pest Management, vol. 19, no. 2, pp. 55–59, 2008.

A. V. Latchininsky and R. Sivanpillai, “Locust habitat monitoring and risk assessment using remote sensing and gis technologies,” in Integrated management of arthropod pests and insect borne diseases. Springer, 2010, pp. 163–188.

K. Cressman, “Role of remote sensing in desert locust early warning,” Journal of Applied Remote Sensing, vol. 7, no. 1, p. 075098, 2013.

A. V. Latchininsky, “Locusts and remote sensing: a review,” Journal of Applied Remote Sensing, vol. 7, no. 1. p. 075099, 2013.

I. Klein, N. Oppelt, and C. Kuenzer, “Application of remote sensing data for locust research and management—a review,” Insects, vol. 12, no. 3, p. 233, 2021.

P. Symmons and K. Cressman, “Desert locust guidelines: biology and behaviour,” FAO, Rome, 2001.

C. Piou, V. Lebourgeois, A. S. Benahi, V. Bonnal, M. el Hacen Jaavar, M. Lecoq, and J.-M. Vassal, “Coupling historical prospection data and a remotely-sensed vegetation index for the preventative control of desert locusts,” Basic and Applied Ecology, vol. 14, no. 7, pp. 593–604, 2013.

M. J. Escorihuela, O. Merlin, V. Stefan, G. Moyano, O. A. Eweys, M. Zribi, S. Kamara, A. S. Benahi, M. A. B. Ebbe, J. Chihrane et al., “Smos based high resolution soil moisture estimates for desert locust preventive management,” Remote Sensing Applications: Society and Environment, vol. 11, pp. 140–150, 2018.

C. Piou, P.-E. Gay, A. S. Benahi, M. A. O. Babah Ebbe, J. Chihrane, S. Ghaout, S. Cisse, F. Diakite, M. Lazar, K. Cressman et al., “Soil moisture from remote sensing to forecast desert locust presence,” Journal of Applied Ecology, vol. 56, no. 4, pp. 966–975, 2019.

C. Chen, J. Qian, X. Chen, Z. Hu, J. Sun, S. Wei, and K. Xu, “Geographic distribution of desert locusts in africa, asia and europe using multiple sources of remote-sensing data,” Remote Sensing, vol. 12, no. 21, p. 3593, 2020.

W. L. Ellenburg, V. Mishra, J. B. Roberts, A. S. Limaye, J. L. Case, C. B. Blankenship, and K. Cressman, “Detecting desert locust breeding grounds: A satellite-assisted modeling approach,” Remote Sensing, vol. 13, no. 7, p. 1276, 2021.
S. Beery, E. Cole, J. Parker, P. Perona, and K. Winner, “Species distribution modeling for machine learning practitioners: A review,” arXiv preprint arXiv:2107.10400, 2021.

D. Gómez, P. Salvador, J. Sanz, C. Casanova, D. Taratiel, and J. L. Casanova, “Machine learning approach to locate desert locust breeding areas based on esa cci soil moisture,” Journal of Applied Remote Sensing, vol. 12, no. 3, p. 036011, 2018.

D. Gómez, P. Salvador, J. Sanz, C. Casanova, D. Taratiel, and J. Casanova, “Desert locust detection using earth observation satellite data in mauritania,” Journal of Arid Environments, vol. 164, pp. 29–37, 2019.

E. Kimathi, H. E. Tonnang, S. Subramanian, K. Cressman, E. M. Abdel-Rahman, M. Tesfayohannes, S. Niassy, B. Torto, T. Dubois, C. M. Tanga et al., “Prediction of breeding regions for the desert locust schistocerca gregaria in east africa,” Scientific Reports, vol. 10, no. 1, pp. 1–10, 2020.

D. Gómez, P. Salvador, J. Sanz, and J. L. Casanova, “Modelling desert locust presences using 32-year soil moisture data on a large-scale,” Ecological Indicators, vol. 117, p. 106655, 2020.

D. Gómez, P. Salvador, J. Sanz, J. F. Rodrigo, J. Gil, and J. L. Casanova, “Prediction of desert locust breeding areas using machine learning methods and smos (mir_smnrt2) near real time product,” Journal of Arid Environments, vol. 194, p. 104599, 2021.

M. Barbet-Massin, F. Jiguet, C. H. Albert, and W. Thuiller, “Selecting pseudo-absences for species distribution models: how, where and how many?” Methods in ecology and evolution, vol. 3, no. 2, pp. 327–338, 2012.

M. Iturbide, J. Bedia, S. Herrera, O. del Hierro, M. Pinto, and J. M. Gutiérrez, “A framework for species distribution modelling with improved pseudo-absence generation,” Ecological Modelling, vol. 312, pp. 166–174, 2015.

Y. Freund and R. E. Schapire, “A decision-theoretic generalization of on-line learning and an application to boosting,” Journal of computer and system sciences, vol. 55, no. 1, pp. 119–139, 1997.

J. H. Friedman, “Greedy function approximation: a gradient boosting machine,” Annals of statistics, pp. 1189–1232, 2001.

L. Breiman, “Random forests,” Machine learning, vol. 45, no. 1, pp. 5–32, 2001.

S. J. Phillips, R. P. Anderson, and R. E. Schapire, “Maximum entropy modeling of species geographic distributions,” Ecological modelling, vol. 190, no. 3-4, pp. 231–259, 2006.

J. Demšar, “Statistical comparisons of classifiers over multiple data sets,” The Journal of Machine Learning Research, vol. 7, pp. 1–30, 2006.

M. Friedman, “The use of ranks to avoid the assumption of normality implicit in the analysis of variance,” Journal of the american statistical association, vol. 32, no. 200, pp. 675–701, 1937.

S. Holm, “A simple sequentially rejective multiple test procedure,” Scandinavian journal of statistics, pp. 65–70, 1979.

S. M. Lundberg and S.-I. Lee, “A unified approach to interpreting model predictions,” in Advances in Neural Information Processing Systems 30, I. Guyon, U. V. Luxburg, S. Bengio, H. Wallach, R. Fergus, S. Vishwanathan, and R. Garnett, Eds. Curran Associates, Inc., 2017, pp. 4765–4774. [Online]. Available: http://papers.nips.cc/paper/ 7062-a-unified-approach-to-interpreting-model-predictions.pdf

H. M. O. A. Samil, A. Martin, A. K. Jain, S. Amin, and S. E. Kahou, “Predicting regional locust swarm distribution with recurrent neural networks,” arXiv preprint arXiv:2011.14371, 2020.

M. Tabar, J. Gluck, A. Goyal, F. Jiang, D. Morr, A. Kehs, D. Lee, D. P. Hughes, and A. Yadav, “A plan for tackling the locust crisis in east africa: Harnessing spatiotemporal deep models for locust movement forecasting,” in Proceedings of the 27th ACM SIGKDD Conference on Knowledge Discovery & Data Mining, 2021, pp. 3595–3604.
PlantVillage, “elocust3m,” https://play.google.com/store/apps/details?id=plantvillage.locustsurvey&hl=en_GB&gl=US, 2020.

S. J. Phillips, R. P. Anderson, M. Dudík, R. E. Schapire, and M. E. Blair, “Opening the black box: An open-source release of maxent,” *Ecography*, vol. 40, no. 7, pp. 887–893, 2017.
Supplementary Material

Countries in study region. Mauritanias, Mali, Egypt, Morocco, Algeria, Sudan, South Sudan, Niger, Eritrea, Senegal, Libya, Western Sahara, Uganda, Tunisia, Cape Verde, Chad, Ethiopia, Kenya, Somalia, and Djibouti.

Dataset details – environmental variables, splits, sizes and features. Temporal variables were extracted from NASA Global Land Data Assimilation System Version 2.1 (GLDAS-2.1) Noah Land Surface Model with a temporal resolution of 3 hours and spatial resolution of 0.25 x 0.25 degrees. https://disc.gsfc.nasa.gov/datasets/GLDAS_NOAH025_3H_2.1/summary

Table 2: Environmental variables and their descriptions

| Name                | Description                                      |
|---------------------|--------------------------------------------------|
| AvgSurfT_inst       | Instantaneous average surface skin temperature (K) |
| Albedo_inst         | Instantaneous albedo (%)                         |
| SoilMoi0_10cm_inst  | Instantaneous soil moisture 0-10cm (kg m⁻²)       |
| SoilMoi10_40cm_inst | Instantaneous soil moisture 10-40cm (kg m⁻²)      |
| SoilTMP0_10cm_inst  | Instantaneous soil temperature 0-10cm (K)        |
| SoilTMP10_40cm_inst | Instantaneous soil temperature 0-10cm (kg m⁻²)    |
| Tveg_tavg           | 3-hour averaged Transpiration (W m⁻²)             |
| Wind_f_inst         | Instantaneous wind speed (m s⁻¹)                 |
| Rainf_f_tavg        | 3-hour averaged total precipitation rate (kg m⁻² s⁻¹) |
| Tair_f_inst         | Instantaneous air temperature (K)                |
| Qair_f_inst         | Instantaneous specific humidity (kg kg⁻¹)        |
| Psurf_f_inst        | Instantaneous surface pressure (Pa)              |

Soil profile variables were extracted from International Soil Reference and Information Centre (ISRIC) SoilGrids250m 2.0 data product. https://data.isric.org/geonetwork/srv/eng/catalog.search#/home

Table 3: Environmental variables and their descriptions

| Name             | Description                                                                 |
|------------------|-----------------------------------------------------------------------------|
| sand_0.5cm_mean  | Average sand content between 0-5cm (g/kg)                                   |
| sand_5.15cm_mean | Average sand content between 5-15cm (g/kg)                                  |
| clay_0.5cm_mean  | Average clay content between 0-5cm (g/kg)                                   |
| clay_5.15cm_mean | Average clay content between 5-15cm (g/kg)                                  |
| silt_0.5cm_mean  | Average silt content between 0-5cm (g/kg)                                   |
| silt_5.15cm_mean | Average silt content between 5-15cm (g/kg)                                  |

Table 4: Dataset splits, sizes and number of features

| Split | Feature type(s) | Number of features | Presence | Pseudo-Absence | Total   |
|-------|-----------------|--------------------|----------|----------------|---------|
| Train | Numeric         | 174                | 17007    | 9251           | 26258   |
| Val   | Numeric         | 174                | 4206     | 2359           | 6565    |
| Test  | Numeric         | 174                | 5842     | 1238           | 7080    |

We used a total of 12 temporal and 6 non-temporal variables. For each temporal variable, we retrieved a 95-day history and removed the last 7 days (including the observation day), to ensure that we predict 7 days ahead. Furthermore, we took each 89-day window and bucketised over time by computing the mean value for every 6-day window. We dropped the last window, which had less than 6 days. After doing this we arrived at 14 windows for each variable, so that in total we had 168 (14*12) temporal features. In addition to 6 non-temporal features the total number of features was 174.

ML model hyperparameters. We performed manual hyperparameter tuning on the validation set resulting in the follow values: a maximum tree depth of 4 for XGBoost and 15 for RF. The number of random variables used for node splitting in RF was \( \sqrt{p}\), where \( p \) is the total number of variables.
For our MaxEnt model, we used a linear feature class and a regularization factor of 1. These hyperparameters were found using a grid search on the training data over the available feature classes (linear, quadratic, product, threshold and hinge) and regularization factor in the range [0.1,1], with a step size of 0.1. We used the MaxNet library from Phillips et al. (2017) for modeling.