An Innovative Early Warning System to Tackle Illegal Deforestation

Anouk VAN STOKKOM, Jorn DALLINGA, Michael DEBUYSER, Dirk HOEKMAN, Boris KOOIJ, the Netherlands, Pablo PACHECO, David THAU, United States, Suzanne VALKMAN and Hans BEUKEBOOM, the Netherlands

Key words: Deforestation, Spatial Planning, Remote Sensing, Predictive Modelling, Machine Learning, Big Data.

SUMMARY

Forest cover loss is a persistent problem with 6,5 Mha lost annually on a global scale in the period from 2010 to 2015 (FAO, 2015). Next to the implications on biodiversity, fauna habitats, and local communities, deforestation causes 11% of the global greenhouse gas emissions of which parts can be attributed to illegal deforestation (FAO, 2018). Current forest monitoring systems using remotely sensed data, are widely available (FAO, 2020). However, to effectively action illegal deforestation these systems are often too reactive, are hampered by cloud cover, or are not inclusively developed, implemented and used by stakeholders in well-defined protocols.

Early Warning Systems (EWS) have the potential to deliver accurate and timely information on likely deforestation events in order to inform decision-making and adoption of response actions. The World Wide Fund for Nature (WWF) is developing an EWS program with the aim to predict deforestation 6 months in advance and enable national and local governments to act on illegal deforestation as early as possible in the deforestation chain. Hence, the approach is two-fold: develop technological predictive capabilities and follow a development and implementation process to ensure proper on the ground enforcement practices.

The EWS program is based on an agile approach which allows the technical and operational feasibility to be tested on a small scale before rolling out to larger landscapes. To this end, a proof of concept (PoC) and pilot were developed by WWF and partners in Central Kalimantan, Indonesia. Initial results look very promising: the technical feasibility of predicting deforestation 6 months in advance of the event was demonstrated through a machine learning model with user's accuracy of ~80% and corresponding detection rate of up to 46%. Secondly, local stakeholders have started in-field interventions leveraging a dashboard that visualizes the deforestation predictions and allows follow up of alerts. Thirdly, several governance mechanisms were set up to further improve intervention protocols, ensure active engagement of local stakeholders. This paper showcases EWS's innovative proposition and set up, discusses early results and provides an overview of next steps.

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1. INTRODUCTION

1.1 Problem statement

Forest cover loss is a persistent problem with 6,5 Million hectares lost annually on a global scale in the period from 2010 to 2015 (FAO, 2015). This is concerning because forests hold a richness of biodiversity by providing vital habitat for fauna, and sustaining an abundance of tree and other vegetation species, some of which are now at the brink of extinction in their original habitat, like teak and orangutans (IUCN, 2020). In addition, forests sustain livelihoods for local people by providing food, fuel and building materials (FAO, 2018). Forests contain enormous genetic diversity, making them resilient to withstand diseases and giving them the potential to provide many, some yet to be discovered, medicines and other applications. In addition, forests play a critical role in regulating climate due to their dual role as sources and sinks of CO_2. When forests are logged and the land is left barren, it is prone to erosion and releases significant amounts of CO_2 and other greenhouse gasses (IPCC, 2019). The yearly rate of deforestation causes 11% of global greenhouse gas emissions, of which parts can be allocated to illegal deforestation. Therefore, regulating logging and forest clearing not only helps to sustain a healthy balance between human activities and nature, but also contributes to the Sustainable Development Goals (SDG) in their aim to mitigate climate change (Katila et al., 2019). Monitoring forest conversion has been identified as a key area for addressing forest cover loss.

1.2 Current approaches

Forest monitoring systems using remotely sensed data, e.g. optical satellite data, are widely available (FAO, 2020).However, to effectively action illegal deforestation these systems are often too reactive (typically event warnings for already occurred deforestation), are hampered by cloud cover, or are not inclusively developed, implemented and used by stakeholders in well-defined protocols.

Figure 1: Photo of recent deforested peatland close to Sebangau National park, Central Kalimantan, Indonesia (Source: WWF-Indonesia, November 2019).

In contrast to deforestation detectors, predictive models, e.g. by the World Resource Institute and Imazon, aim to anticipate deforestation (the left hand side of Figure 2). These models predict deforestation years in advance and focus on producing long term risk maps for strategic decisions addressing policies and spatial planning. However, none of the existing models (to our knowledge) intends to include short-term predictions of risks weeks or months before the likely occurrence of deforestation events, while at the same time ensuring a high enough spatial accuracy in order to allow for actionable interventions on the ground. The lack of available and timely alerts on the local level, makes it difficult to ensure compliance with existing regulations as a way to deter deforestation, part of which is illegal. The different actors responsible to take action are informed too late or not at all, which hinders their capacity to react in a timely and adequate manner. By the time they arrive at the scene the damage has already been done and the offenders and trees might be gone.

Figure 2: Different model types of Early Warning Systems known to WWF, based on a market overview assessment at the end of 2018.

1.3 Early Warning System for predicting deforestation

Early Warning Systems (EWS) have the potential to deliver accurate and timely information on likely deforestation events in order to inform decision-making and adoption of response actions. The World Wide Fund for Nature (WWF) is developing an Early Warning System (EWS) program with the aim to predict deforestation 6 months in advance and enable national and local governments to act on illegal deforestation as early as possible in the deforestation chain. Hence, the approach to the two-fold problem is a two-fold solution: develop technological predictive capabilities and follow a development and implementation process that ensures the technological part of the system is well embedded in on the ground enforcement practices.

The EWS is in the early stages of development, but the initial results look very promising. This paper introduces the EWS by showcasing its innovative proposition and set up. Below we share the main achievements and next steps along with a description of the main foreseen opportunities and challenges.

2. THE EWS PROGRAM

2.1 Approach

The EWS program constitutes an innovative solution combining a technological advanced risk model and geospatial big data, including the latest technology on satellite imagery and information on human activity, such as road development and land use change. Next to the technical development of the solution, the EWS program aims at engaging local stakeholders, like local and national governments, NGOs, CSOs and Universities, to make the solution fit for purpose, and also support the development of onsite interventions and integration with traditional surveys, such as deforestation patrolling exercises.

With the EWS, decision-makers can anticipate when deforestation is going to happen, identify whether it is illegal, prioritise the deforestation predictions and plan interventions accordingly. This allows e.g. law enforcers, national park rangers and land surveyors to improve their effectiveness in protecting forested areas where the risk and impact of potential illegal deforestation is high. The time between an alert and the intervention, the so called "lead time", is reduced ideally to such a degree that the interventions take place before the deforestation happens. This in turn will reduce illegal activities and deter future offenders. Moreover, motives for land clearance can be addressed and local communities and businesses can be stimulated to choose other paths. Furthermore, ensuring transparency[1] of alerts, interventions and their effectiveness, is important to allow for informed decision making by all involved stakeholders that have different interests and priorities in the landscape.

The EWS program is based on an agile, iterative approach to allow the technical and operational feasibility to be tested on a small scale before scaling up to larger spatial extents

[1] The EWS program follows 7 guiding principles in its development, which includes, amongst others, the transparency of the system and the monitoring of potential adverse social and environmental effects of EWS.

and roll-out to other geographic landscapes. The local implementation is led by a local host to ensure local ownership and informed by users, including governments at different levels, local communities, private companies and NGOs. Supported by WWF and its partners, the intention is that these stakeholders are responsible for the implementation and maintenance themselves. Together with local stakeholders, local contextual data is collected, some of which can also feed into the models to improve the predictive model or prioritisation process.

2.2 Background on EWS initialisation and partnerships

WWF joined forces with the Boston Consulting Group (BCG) to explore how data and technology could solve the most urgent conservation challenges including the difficulty of protecting forests in landscapes undergoing active deforestation. As part of their global partnership, WWF and BCG decided to shape a program aimed at predicting deforestation and improve local enforcement practices to put an halt to illegal logging: the 'Early Warning System'.

As a first step a Proof of Concept (PoC) was developed in 2018 to test the feasibility of the technology and check operational relevance of such a tool on the ground in Indonesia. For this, a region of 50*80 km near Palangkaraya, located in Central Kalimantan on the island of Borneo, Indonesia, was selected due to stable political relationships amongst local stakeholders, active ongoing illegal deforestation, data availability and capacity on the ground.

After the concept was successfully proven, a prototype for the medium-term forecasting has been developed in 2019, to scale and test the predictive technology of such a tool to a larger area (Central Kalimantan, Figure 3). SarVision was contracted to process raw radar data. In parallel a governance structure with relevant stakeholders (national and local) was put in place. At the end of 2019 the partnership has been expanded to include a consortium led by Deloitte with AWS, Jheronimus Academy of Data Science and Utrecht University to scale the EWS technology to Borneo and other landscapes, to improve the accuracy of the predictions and enhance the usability of the tool.

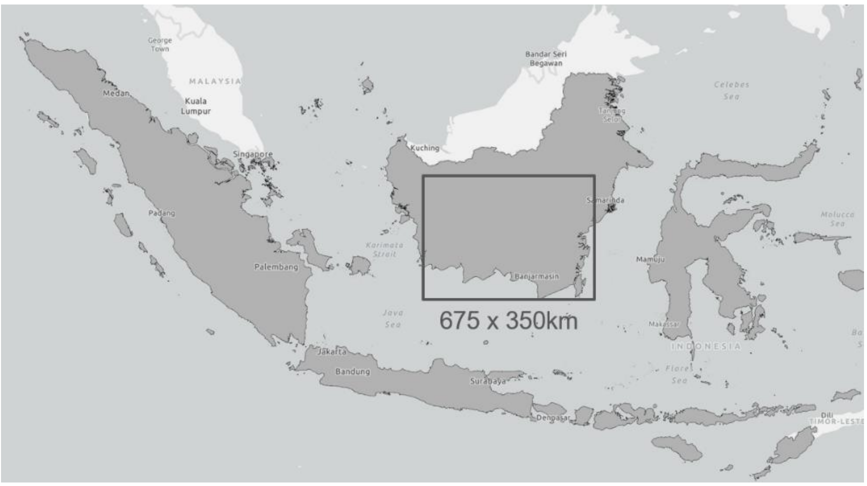

Figure 3: EWS prototype area (bounding box) in Central Kalimantan on Borneo, Indonesia.

3. METHODS AND DATA

The EWS program comprises the complete process from raw data to prediction to decision making and law enforcement. Figure 4 shows the main components within the information landscape. In the first step, deforestation alerts are generated through machine learning and published to a dashboard (step 1). The primary data source for the EWS is a set of labelled radar satellite images representing historic degradation and deforestation events. Additional geographic big data sets are explored to generate spatial predictive indicators for deforestation. This data sourcing and preprocessing step results in input data for the model. With machine learning, models are tested on performance of deforestation prediction and the best performing machine learning model produces predictions and subsequently alerts. Forest cover risks maps indicate which areas are in heightened risk of deforestation within 6 months (step 2). These risk maps consist of deforestation predictions that require prioritisation, such as determining the legality of imminent deforestation and the value (e.g. biodiversity or carbon) of the areas, in order to develop concrete and practical interventions to prevent illegal deforestation. Subsequently, deforestation alerts are investigated in the field and appropriate interventions are taken. To ensure the feedback loop to the modelling and alerts and steer long term policy making, the impact of interventions is monitored and analysed.

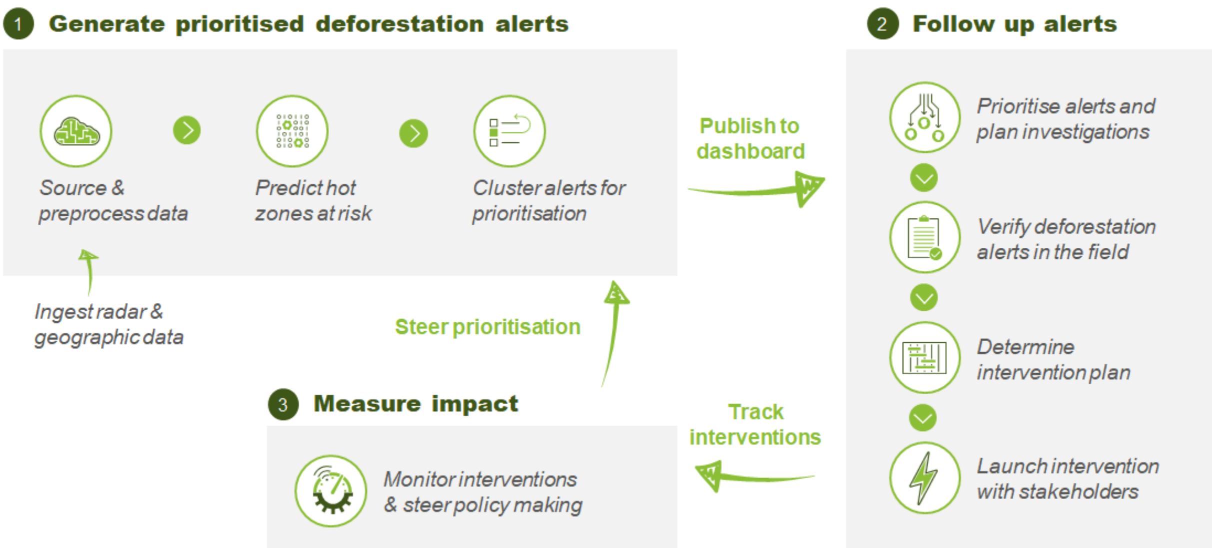

Figure 4: Schematic view of end-to-end EWS flow.

3.1 Generate prioritised deforestation alerts

3.1.1 Data Sourcing and Preprocessing

Open source dynamic, semi-dynamic and static geographical data are collected. This includes data on for example settlements, grey and blue infrastructure and mining concessions. The data is cleaned and preprocessed to fit the models need. Data on deforestation and forest degradation is not readily available and needs to be processed from raw radar data (Hoekman et. al, 2020).

For data on forests, free ESA Sentinel-1 radar data in SLC format are automatically downloaded from data portals as soon as available. Since 2017 there are two identical Sentinel-1 radar satellites in a 12-day orbit. Therefore, two observations can be made within the 12-day repeat cycle. In most areas of the world one observation is made. In the future, two observations will be made in more areas, which increases the observation frequency from once every 12 days into once every 6 days. At the moment Borneo is still observed only once every 12 days.

Interferometric processing is used for radiometric calibration and geometric correction. State-of-the-art slope correction algorithms and multi-temporal speckle reduction algorithms (developed by Wageningen University and SarVision) are applied to improve the quality and usefulness of the data. The result is an (updated) time-series of dual-polarization (VV- and HV-) intensity images at a 15-meter pixel size.

Change detection is done with respect to the oldest Sentinel-1 radar images. Land cover baseline maps are based on available radar and optical images around the start of the Sentinel-1 data acquisition period. Radar images used usually are the Sentinel-1 (C-band) and PALSAR-2 (L-band); optical images used include Sentinel-2 (when available) and Landsat-8. The thematic processing chain is divided into an historical part (for all already available Sentinel- 1 images) and a near real-time part (for all newly available Sentinel-1 images). The historical analysis provides good insights in the nature and location of changes in recent years. State-of-the-art time-series analysis algorithms (developed by Wageningen University and SarVision) are applied to monitor changes in forest cover in terms of deforestation and degradation. Salient features are the use of object-based changes and the use of feedback loops to increase sensitivity while at the same time reducing noise. New models have been developed and validated to quantify the intensity of the degradation. Line detection techniques are used to improve mapping of linear features, such as the illegal roads and canals in peat swamp forest.

The radar observation yields three distinct types of information, which all need validation for a range of different landscapes. The information types are clear-cut deforestation, degradation and canal/roads. Results depend on forest type and terrain type. In particular, distinction has to be made between wetland forest, peatland forest, dryland forest on flat to undulating terrain and forest in mountainous areas. Early results show that accuracy of clear-cut deforestation detection is very high in general (90-95%), but that near real time detection in peat swamp forest is sometimes delayed during wet conditions. The accuracy of canal/road detection in flat areas, such as peat swamp forest is high (85%) and even large fractions of the smallest canals (6 m wide) are detected. Small-scale degradation (such as selective logging) is often well visible in radar images but not in optical images and, therefore, still hard to validate. A careful qualitative time series analysis, considering context and sparse evidence from other satellite data, may lead to the conclusion that degradation can be mapped and quantified well. Even though the accuracy is not well known, the possibility of degradation detection in an early stage with radar, which is often a precursor to major disturbances, is of paramount importance to early warning.

3.1.2 Machine learning to predict hot zones at risk

Three classes of models were built, trained and tested. These classes are ensemble trees, support vector machine and neural networks. The historic deforestation data, combined with the open source data, is separated into two sets to be used for the model; one is used for training purposes, the other set is used for validation on historic events. The training data feeds the model to recognise patterns between new deforestation and other spatial elements using quantitative analyses. Based on the predictive power of these elements and validation on historic events they are selected to be deployed together with historical deforestation data to predict new deforestation on a scale of 15 * 15 meter. However, this high spatial resolution represents about the size of the crown of a large tree (MacKinnon et. al, 1997), while the model is not expected to predict at such high spatial accuracy considering the practical implementation of investigation alerts or protocols. Subsequently, the predictions are down-sampled to 480 * 480 meter so called "hot zones" (Figure 5).

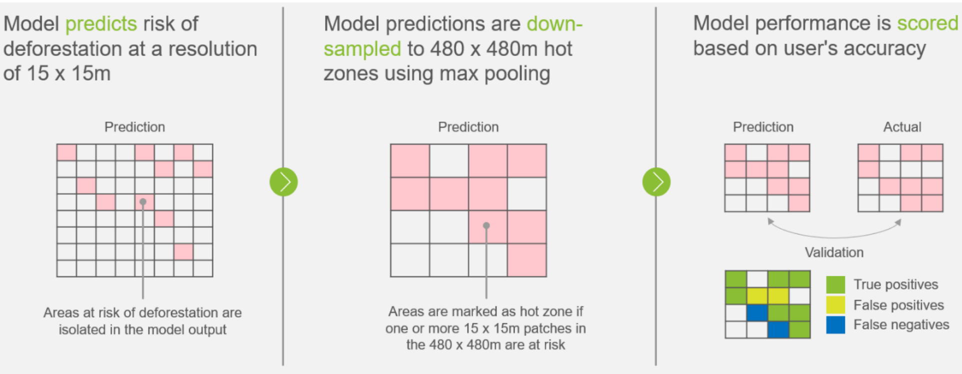

Figure 5: Diagram illustrating post-processing of predictions to hot zones.

3.1.3 Cluster alerts for prioritisation

To facilitate prioritisation in the next step, the hot zones are clustered together (Figure 6). The spatial clustering algorithm assigns hot zone centroids to clusters based on proximity to other hot zones and is further constrained by forest ownership and other variables. These clusters are visualised in a dashboard along with their cluster density index (CDI).

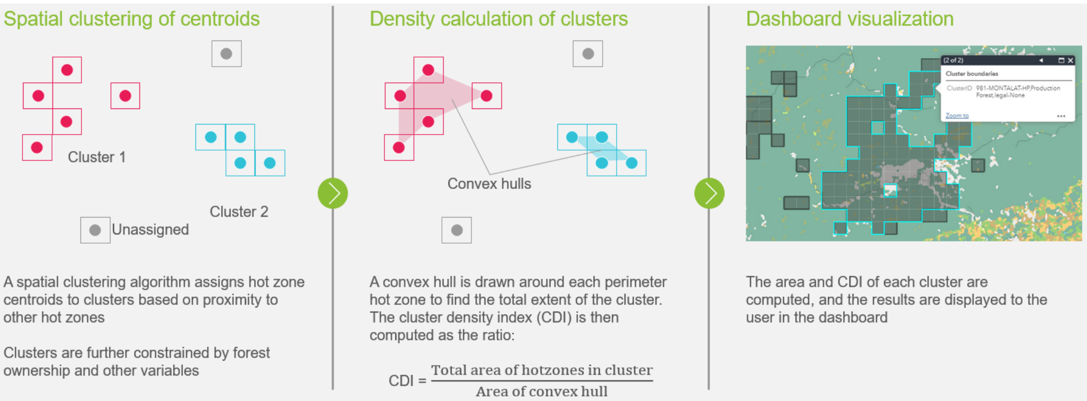

Figure 6: Clustering of predictions to aid in prioritisation.

3.2 Follow up alerts

The predictions (or hot zones) from the model are converted into alerts to form a forest cover risk map depicted in a map-based dashboard. We consider all the output from the model where the risk for deforestation is above a varying threshold as predictions. Alerts, however, are actionable predictions with an intervention protocol to prevent illegal deforestation. The dashboard provides decision-makers with insight into up to date alerts and clusters. Within this environment, the clusters are prioritised, where the distinction between legal and illegal deforestation with local data is of utmost importance. Moreover, the dashboard includes contextual data to improve interpretation by the decision-makers. This includes standard global data, for example elevation and soil type data. It is also possible to add customisable data. This provides the opportunity to add local contextual data to the dashboard, such as national park boundaries and palm oil concessions.

Investigations are carried out for the prioritised clusters. Land surveyors validate if the first signs of deforestation are already visible on-site or if there is reason to believe it will start in the near future. Reporting back on their findings, the alerts are shortlisted according to the highest threats. Strategic and customisable intervention protocols are set into place to prevent the predicted deforestation. Possible interventions could include focussed patrols, camera traps and influencing land use planning by, for example, local stakeholder engagement.

3.3 Measure impact

The impact is measured according to reduced illegal deforestation. EWS's performance is validated against a control area on the following aspects: for the differences of actual deforestation in percentages in areas where interventions has taken place, the performance of the model on predicted and not predicted with reality 6 months afterwards and statistics on executed interventions in comparison with the number of alerts.

4. RESULTS

This result section describes the intermediate results from the PoC and prototype phase of the Early Warning System program. In the meantime, development continues.

4.1 Generate prioritised deforestation alerts

The model tests concluded that the ensemble trees model, or more specifically, the gradient boosted trees algorithm, is the most optimal model with the highest accuracy. This algorithm combines multiple decision trees to predict deforestation. Each tree uses the results of prior trees to minimise the (remaining) prediction error.

The medium-term forecasting model achieved 80% user's accuracy along with 20% detection rate across the entire study area. The user's accuracy is calculated by dividing the total number of correct deforestation predictions by the total amount of predictions.

The alerts are plotted on a map-based dashboard in an ESRI-environment (Figure 7). Here, also historic and recent deforestation and contextual data are shown (Figure 8).

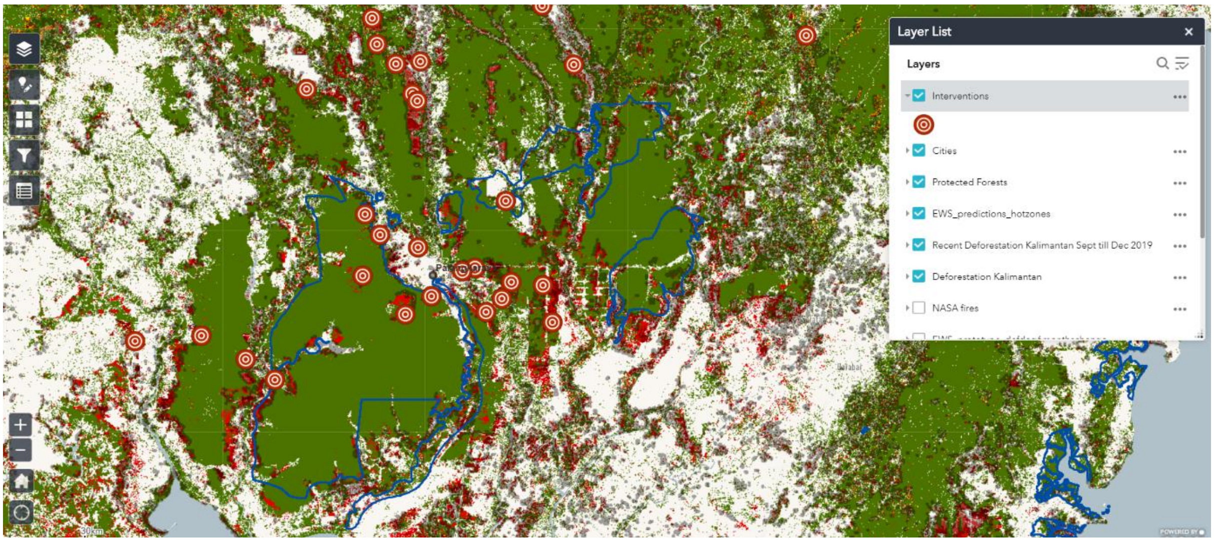

Figure 7: An impression of the dashboard.

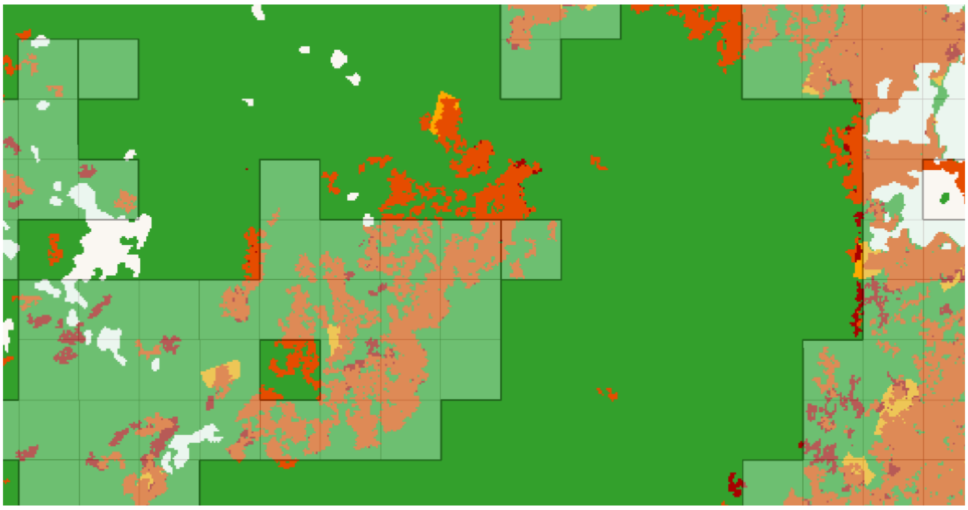

Figure 8: Deforestation history (red) and forest degradation history (orange) (2015 till March, 2019), recent deforestation (dark red) (August, 2019) and prediction hot zones (squares) (August, 2019 - February, 2020).

4.2 Follow up alerts

Together with local stakeholders such as national parks and government institutes, WWF has launched a pilot in Central Kalimantan. This ongoing pilot aims to validate deforestation alerts, define and improve intervention protocols, further refine the dashboard and models based on user feedback and to have an impact on preventing illegal deforestation. With success, several field validations with local stakeholders were made (in November 2019) to ensure actual deforestation could be observed for predicted hot zones.

5. DISCUSSION

5.1 Trade-off user's accuracy versus detection rate for selected model

The output of the prediction model is a probability of deforestation. To determine which probability of deforestation is high enough to label it as a prediction, a threshold value is used. When setting this threshold there is a trade-off between user's accuracy (precision) and detection rate (sensitivity). User's accuracy indicates if the outputted predictions actually occur 6 months within the hot zone later after the prediction. The detection ratio shows the rate between the actual occured deforestation and which ones were predicted 6 months before. User's accuracy increases when the threshold for the probability is increased, but this negatively affects the detection rate. Figure 9 shows this relation.

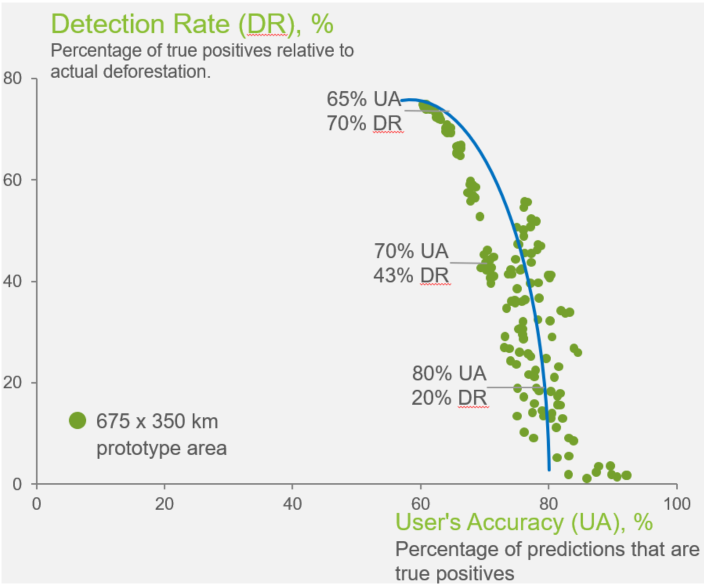

Figure 9: Relation between user's accuracy and detection rate.

We have set the acceptance level for user's accuracy and detection rate on 80% and 20% respectively. Since time and resources are limited by local stakeholders to follow up on deforestation alerts, a high user's accuracy is important to limit the amount of costly investigations as much as possible. On the other hand, missing areas of high risk deforestation may lead to destruction which could otherwise have been prevented. To minimise these risks the model is being further enhanced to improve the user's accuracy and detection rate and find the most optimal balance. Since the prototype phase, the detection rate has already been improved from 20% up to almost 46% for a similar user's accuracy, and further improvements are ongoing. The quality of data sources is improved, additional data sources are tested, and other model techniques, like deep learning methods, are explored. Moreover, the three model classes tested before, ensemble trees, support vector machine and neural networks, will be tested more in depth. Beside model optimisation, the validation process of the predictions needs to be carefully designed and is under construction. Moreover, the success of interventions is measured in the absence of deforestation events, the forests are exactly as they were before, while ensuring the causal relation between interventions and this unchanged status of the forests. The validation process needs to be designed in such a way that it accounts for these and other difficulties, in order to obtain a representable result of the success of the model and the interventions.

5.2 Continuation of EWS pilot

A Project Management Office (PMO) has been formed involving local stakeholders with the development of the EWS. Investigation protocols have been set up and are currently implemented for the pilot. Moreover, discussions on intervention protocols have started. In parallel, an user board is being set up with a.o. local NGOs, CSOs and local universities to foster inclusion, capture feedback and priorities of the different stakeholders.

The viability and success of EWS are measured according to the accuracy of the predictions, implementation and the resulting impact of the end to end approach on avoided deforestation. Implementation is considered a success when EWS is accepted and installed within the assigned landscape. As the pilot is still ongoing, the impact was not yet quantified.

To estimate the potential impact of the EWS, we performed interviews with region experts and, for each deforestation driver, estimated the share of forest loss that could be predicted, the share of alerts that could be acted on, and the effectiveness of interventions. Based on this analysis, we estimated EWS could realise a yearly reduction in illegal deforestation of 10 to 30% by 2022, corresponding to an avoidance of up to 260 thousand ha of forest or 200 million tCO_2 emissions for Borneo and Sumatra.

5.3 Implementation and risks associated with a predictive system

The EWS strives to have a positive impact on nature as well as human livelihoods. Risks for unwanted and unforeseen negative side effects need to be assessed, to be able to prevent or mitigate these risks as much as possible. The response of individuals and local communities are difficult to predict and might differ per landscape. Behavioural changes might be counterproductive and could lead to misuse of the system. For example, if potential offenders have insight for which areas alerts have been given out, they might shift their plans to other areas. Another possible outcome is social and economic instability. A response to monitoring with big data and accusations before the actions are even attempted, could be rebellious of nature or causing a division within communities. Moreover, due to the transparency of the EWS, divisions between different levels of governments might be revealed which could sharpen tensions and could lead to conflicts. For example, boundaries of national parks might differ between national and local governments or local permits might not be recognised at the central level, meaning the distinction between legal and illegal logging is not in all cases evident. More risks with the implementation could include unclear mandates, insufficient resource allocation and corruption. We set up a process to identify and mitigate these risks through a WWF risk register method which includes regular revisits of risk exposure.

5.4 Scaling challenge

The 11 deforestation fronts WWF's Living Forests Report (2015) identifies where 80% of the deforestation between 2010 and 2030 is likely to happen. These deforestation fronts are on top of EWS's priority list to roll out the system (Figure 10). EWS will roll out based on social and political opportunities in some of the deforestation fronts, but only when the risks can be mitigated and fall within the accepted tolerance.

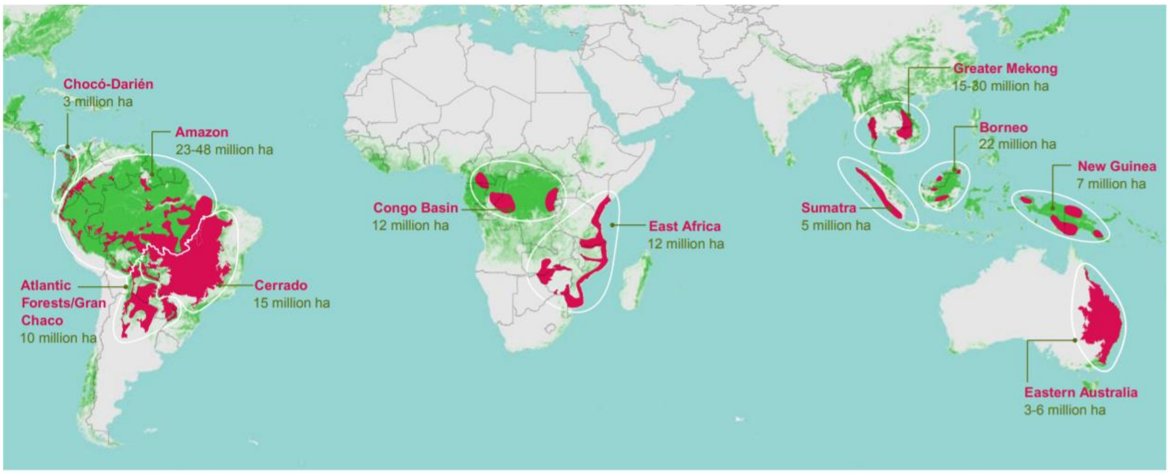

Figure 10: Worldwide forests (green) and the 11 deforestation fronts, with projected forest losses between 2010 – 2030 (red). (WWF's Living Forests Report, 2015).

Although the 11 deforestation fronts, also take other factors besides illegal deforestation into account, it remains an indication of the enormous potential EWS has. To be able to initiate EWS around the world, a scalable open-source solution is necessary. For this purpose, the EWS model is further improved by optimising the technical architecture, resulting in less costs and computing time. For the latter, the focus is on preventing a linear relation between increased data input and computing time. To illustrate, when twice the amount of data goes into the EWS model, this should not result in twice the amount of computing time. Moreover, the model will have a standardised modular set up. Therefore, it is possible to tweak, for example, indicators and parameters to the local context wherever it is implemented. Output from the model will be automatically updated in the dashboard. The dashboard is going to be a custom made, scalable and fully integrated solution for the alert tracking step.

5.4 Next steps on technology

The EWS programme has focussed so far on a 6 months medium-term predictive model. In the future also a reactive and a short-term predictive model will be tested for feasibility and could complement the medium-term predictions in terms of additional possible interventions suitable for these types of predictions. The short-term model predicts 1 to 4 weeks where high risk deforestation hot zones will occur to support preventive measures such as rerouting of patrols. The last one is the reactive model (using radar technology) which covers near real-time detection of illegal activities within 1-4 weeks to support more timely enforcement.

As the medium-term predictive model and its technology solution become embedded in the local deforestation prevention protocols, WWF and partners will jointly decide on an ownership model for the system. Interested parties such as governments, NGOs and universities are sought to further implement, scale and enhance the technology.

6. CONCLUSION

EWS has formed its shape; the model is already reaching the aimed accuracy, the dashboard will guide decision-makers to prioritise alerts in the pilot area and the system as a whole is embraced by local stakeholders for implementation. Within a year, the first impact on reduced deforestation is expected to become reality. Further collaboration with local stakeholders, tech- and consultancy partners will enhance the EWS even more and applicable and suitable for larger areas and other landscapes. Challenges that have the focus in the next steps of EWS are the integration of feedback from (local and national) stakeholders, transparency of the system and its results and the further development of actionable protocols to prevent illegal deforestation. The resulting outstanding quality of the model performance and inclusive approach, enables national and local governments, law enforcers and local communities to rely on the system and feel ownership.

7. ACKNOWLEDGEMENTS

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CONTACTS

Name: MSc. Jorn Dallinga and MSc. Anouk van Stokkom

Institution: World Wide Fund for Nature (WWF), Netherlands

Address: Driebergseweg 10

City: Zeist

COUNTRY: The Netherlands

Tel.: 0800 1962

Email: ews@wwf.nl