An Innovative Early Warning System To Tackle Illegal Deforestation

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SUMMARY

Forest cover loss is a persistent problem with 10.2 Mha gross deforestation annually on a global scale in the period from 2015 to 2020 (FAO, 2020[1]). Besides implications for 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, 2020[2]). Forest monitoring systems that use remotely sensed data are widely available (FAO, 2020[3]). To effectively curb illegal deforestation however, 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 interventions. The World Wide Fund for Nature (WWF) is developing an EWS program with the aim to predict deforestation 6 months in advance to enable national and local governments to act on illegal deforestation as early as possible in the chain of deforestation events. Hence, the approach is two-fold: 1) develop technological predictive capabilities and 2) 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. Local stakeholders have started in-field interventions leveraging the EWS dashboard that visualizes the deforestation predictions and allows follow-up of alerts. Several governance mechanisms were set up to further improve intervention protocols, ensuring active engagement of local stakeholders. Encouraged by the promising uptake of the system, the EWS program is currently being rolled out for further pilots within the landscapes of Sarawak (Malaysia), Gabon, Suriname and Guyana. Calibrating and applying the predictive deforestation model to these respective landscapes resulted in good model performance across all landscapes (>80% User's accuracy and 40-50% detection rate). This paper showcases EWS's innovative proposition and setup, discusses preliminary results and provides an overview of the next steps.

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1. INTRODUCTION

1.1 Problem statement

Forest cover loss is a persistent problem with 10.2 Mha gross deforestation annually on a global scale in the period from 2015 to 2020, with the largest portion in the tropics (FAO, 2020[1]). This is concerning because forests hold a richness of biodiversity by providing vital habitat for fauna and sustaining an abundance of tree and other plant species, some of which are now on the brink of extinction in their native habitat, such as teak and orangutans (IUCN, 2020). In addition, forests sustain livelihoods for local people by providing food, fuel and building materials (FAO, 2020[2]). 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 has the potential to help sustain a healthy balance between human activities and nature conservation, 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.

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

1.2 Current

approaches

Forest monitoring systems using remotely sensed data, e.g. optical satellite data, are widely available (FAO, 2020[3]). These systems are often too reactive however to effectively prevent illegal deforestation, as they typically provide event warnings for already occurred deforestation. Moreover, such systems are often hampered by cloud cover, or are not inclusively developed, implemented and used by stakeholders in well-defined protocols. In contrast to monitoring systems, predictive deforestation models, e.g. by the World Resource Institute and Imazon, aim to anticipate deforestation before it has occurred (the left-most panel of Figure 2). These models predict deforestation years in advance and focus on producing long term risk maps for strategic decision-making addressing policies and spatial planning.

None of the existing models (to our knowledge) attempts to include short-term predictions of risks weeks or months before potential deforestation or degradation events, while at the same time ensuring an adequate spatial accuracy for actionable interventions on the ground. The lack of available and timely alerts on the local level, impedes compliance with existing regulations as a way to deter deforestation, part of which is illegal. Those responsible for law enforcement 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 both offenders and trees are likely 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 interventions. 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 chain of deforestation events. The approach is two-fold: 1) develop a technological solution with predictive capabilities and 2) follow a development and implementation process that ensures the technological part of the system is well embedded in on-the-ground enforcement practices.

This paper introduces the EWS by showcasing its innovative proposition and setup. 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 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 shaped a program aimed at predicting deforestation and improve local enforcement practices to put a halt to illegal logging: the ‘Early Warning System’.

A Proof of Concept and a subsequent prototype were developed in a region near Palangkaraya and scaled up to Central Kalimantan on the island of Borneo, Indonesia, in respectively 2018 and 2019.

At the end of 2019 the partnership was expanded to include a consortium led by Deloitte consisting of AWS, Jheronimus Academy of Data Science and Utrecht University to 1) scale the EWS technology to the whole of Borneo (i.e., including Sarawak, Malaysia) and other landscapes (starting with Gabon, Suriname and Guyana); and 2) improve the accuracy of the predictions and enhance the usability of the tool. SarVision was contracted to process raw radar data for Kalimantan, Sarawak, Guyana and Suriname. For Gabon and the Congo Basin, Wageningen University & Research (WUR) and Global Forest Watch (GFW) contributed to the programme by providing processed radar alert data (Reiche et al., 2021).

2.2 Approach

The EWS program constitutes an innovative solution combining a technologically 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. Besides the technical development, the EWS program engages local stakeholders, such as local and national governments, NGOs, Civil Society Organizations (CSOs) and universities, to make the solution fit for purpose. The system also supports the development of on-site 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 law enforcers, national park rangers and land surveyors, for instance, to improve their effectiveness in protecting forested areas. The time between an alert and the intervention, the so called “lead time”, is ideally reduced so that interventions take place before deforestation happens and therefore the system helps to tackle illegal activities and deters future offenders. Interventions can address motives for land clearance, while local communities and businesses can be stimulated to make more sustainable and green choices. Furthermore, it is important to ensure the transparency[1] of alerts, interventions and their effectiveness, to allow for informed decision-making by all involved stakeholders (who may have different interests and priorities) within the landscape.

The EWS program uses an agile, iterative approach to enable testing of the technical and operational feasibility on a small scale before scaling up to larger spatial extents and rolling out to other geographic landscapes. Local hosts lead the implementation to ensure local ownership, and are informed by end-users, including governments at different levels, local communities, private companies and NGOs. Supported by WWF and its partners, the intention is that these stakeholders become responsible for the implementation and maintenance themselves. In collaboration with local stakeholders, local contextual data is collected and selected to complement the data feeding into the models to improve the predictive model and prioritisation processes.

3. METHODS AND DATA

3.1 Overview

The EWS program comprises a comprehensive pipeline, starting from raw data through predictions to decision-making and law enforcement. Figure 3 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 is a set of labelled radar satellite images representing (recent) historic degradation and deforestation events. Additional geographic big datasets are explored as spatial predictive indicators for deforestation. This data sourcing and pre-processing step results in input data for the machine learning model. Through machine learning, predictive performance of numerous models is compared, and the best performing model is selected to produce predictions and subsequent alerts on the dashboard. The resulting forest cover risks maps indicate which areas are at heightened risk of deforestation within the next 6 months (step 2). These risk maps consist of deforestation predictions that require prioritisation, for instance, by determining the legality of imminent deforestation and the value of the areas (e.g., biodiversity or carbon stock), in order to develop concrete and practical interventions to prevent illegal deforestation from materialising. Subsequently, deforestation alerts are investigated in the field and appropriate interventions are made. To ensure feedback into the modelling and alerts, and steer long term policy, the impact of interventions is monitored and analysed.

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

Figure 3: Schematic overview of end-to-end EWS workflow.

3.2 Generating prioritised deforestation alerts

3.2.1 Sourcing and Pre-processing data

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 pre-processed to fit the model's need. Data on deforestation and forest degradation is not readily available and needs to be generated from raw radar data (Hoekman et. al, 2020). Data products are selected or produced per landscape based on availability and costs.

For data on forests, free ESA Sentinel-1 radar data are deployed. 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, however, currently only one observation is made. In the future, two observations will be made in more areas, which would increase the observation frequency from once every 12 days into once every 6 days.

Based on these datasets, the WUR has produced a map of deforested and degraded land in Gabon, which is used as input for the EWS in this country. For details, see Reiche et al. (2021).

The Sentinel-1 data for Kalimantan, Sarawak, Surinam and Guyana is processed for the EWS by SarVision. 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 the WUR 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 the available radar and optical images from around the start of the Sentinel-1 data acquisition period. Radar images commonly used 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 a historical part (for all historical Sentinel-1 images) and a near real-time part (for all newly acquired Sentinel-1 images). The historical analysis provides good insights into the nature and location of changes in recent years. State-of-the-art time-series analysis algorithms (developed by the WUR 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.

Radar observation yields three distinct types of information, which all need to be validated in a range of different landscapes. These information types are clear-cut deforestation, degradation and canals/roads. Results depend on forest type and terrain type. In particular, a 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 (6m. 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, is necessary to better quantify the performance of radar technology in detecting forest degradation. Even though the accuracy is not yet well known, the possibility of radar technology for early-stage forest degradation detection, which is often a precursor to major forest disturbance, is of paramount importance to early warning. Processing techniques are continuously improved, of which the EWS may make use in the future.

3.2.2 Predicting hot zones

Three classes of models were built, trained and tested; ensemble trees, support vector machine and neural networks. The historic deforestation data, combined with the open-source data, is separated into two sets as input for the model. One set is used for training purposes, the other set for validation on historic events. The training data feeds the model to recognise relationships 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 at a 15-meter resolution. This resolution represents about the size of the crown of a large tree (MacKinnon et. al, 1997). However, the model is not expected to predict at such high spatial accuracy. Therefore, the predictions are down-sampled through max-pooling to 480-meter resolution so-called “hot zones” (Figure 4). Max-pooling means that the hot zone gets assigned with the maximum value occurring within the hot zone. Thus, if one or more pixels within the hot zone is flagged as predicted deforestation, the hot zone is marked as predicted deforestation.

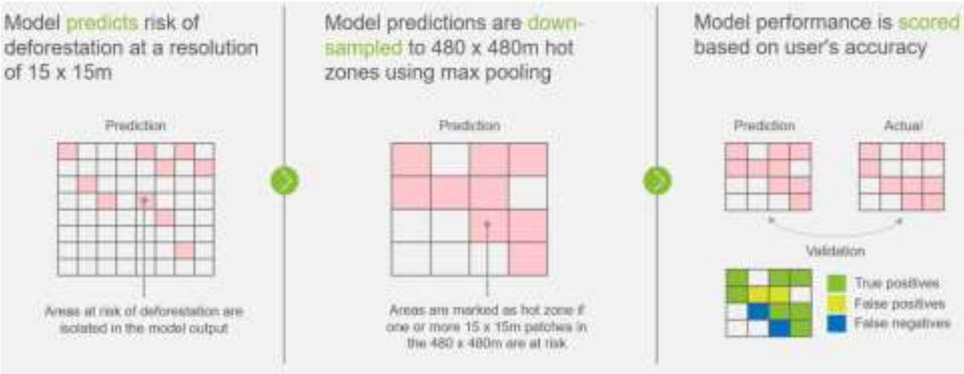

Figure 4: Diagram illustrating post-processing of predictions to hot zones.

3.2.3 Clustering alerts for prioritisation

To facilitate investigation prioritisation in the next step, the hot zones are grouped together in clusters (Figure 5). 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).

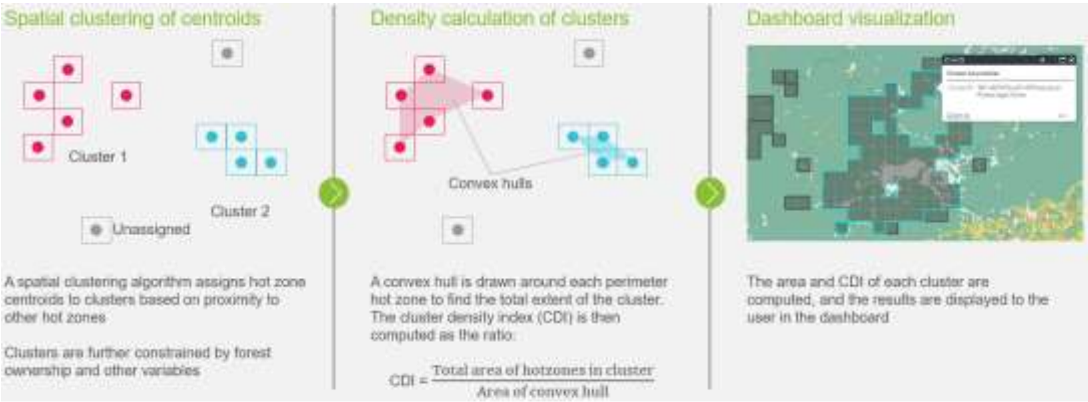

Figure 5: Clustering of predictions to aid in prioritisation.

3.3 Following up on alerts

The hot zone clusters are converted into alerts to form a forest cover risk map depicted in a map-based dashboard in a Mapbox environment (Figure 6). We consider all the output from the model where the risk of deforestation is above a certain threshold to be predictions. Alerts, however, are actionable predictions with an intervention protocol to prevent illegal deforestation on the ground. The dashboard provides decision-makers with insight into up-to-date alerts. Within this environment, the alerts are prioritised, where the distinction between legal and illegal deforestation with local data is of utmost importance. Moreover, the dashboard includes contextual data and historic and recent deforestation 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 custom data. This provides the opportunity to add additional local contextual data to the dashboard on, for example, concessions or land ownership.

Figure 6: The demo-dashboard of Sarawak. Information on this dashboard is illustrative and solely for the purpose of giving an impression of the dashboard environment and does thus not reflect the reality.

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.

3.4 Measuring impact

The viability and success of EWS are measured according to three Key Performance Indicators: adoption, effectiveness and impact. Adoption is measured as the usage of the EWS tools and protocols by stakeholders; effectiveness is measured as the number of successful interventions; and impact assesses the results of these interventions which ultimately should lead to a decrease in illegal deforestation. The latter metric consists of a quantitative approach to determine if in the 6 months after investigations, deforestation is significantly lower than expected based on deforestation trends and control sites.

4. RESULTS AND DISCUSSION

4.1 Prioritised deforestation alerts

Performance is measured against user's accuracy and detection rate. The user's accuracy shows the rate between the total number of correct predicted deforestation and the total number of predicted deforestation (e.g. 50% UA means that of 50% of all predicted deforestation turned out to be deforestation). Predictions are considered correct when deforestation is detected for one more pixels within the hot zone with the 6 months' timeframe. The detection rate shows the percentage of all deforestation that we were able to predict (e.g. 50% DR means we were able to detect 50% of all deforestation). Both criteria were evaluated on 480x480m. hot zones.

The gradient boosted trees algorithm from the open-source software library 'XGboost' performed better than other tested algorithms (higher user accuracy at similar detection rates, and higher detection rate at similar user 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 40% to 50% detection rate across all landscapes.

Figure 8 shows in three steps how the predictions help users to focus their attention to areas in need for interventions. If one does not intervene more deforestation and degradation is the result, step 3.

4.2 Trade-off between user's accuracy and detection rate for selected model

The output of the predictive 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 increases when the threshold for the probability is increased, but this negatively affects the detection rate. Figure 7 shows this relation.

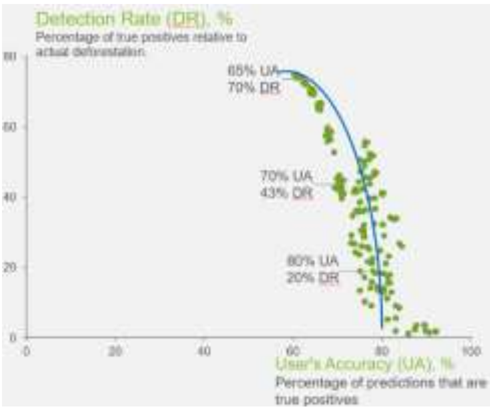

Figure 7: Example relation between user's accuracy and detection rate. Note: this figure merely aims to illustrates the relation and is not portraying the actual model performance.

We have set the acceptance level for user's accuracy and detection rate on 80% and 40 - 50% 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 and input data are optimised per landscape to balance the user's accuracy and detection rate.

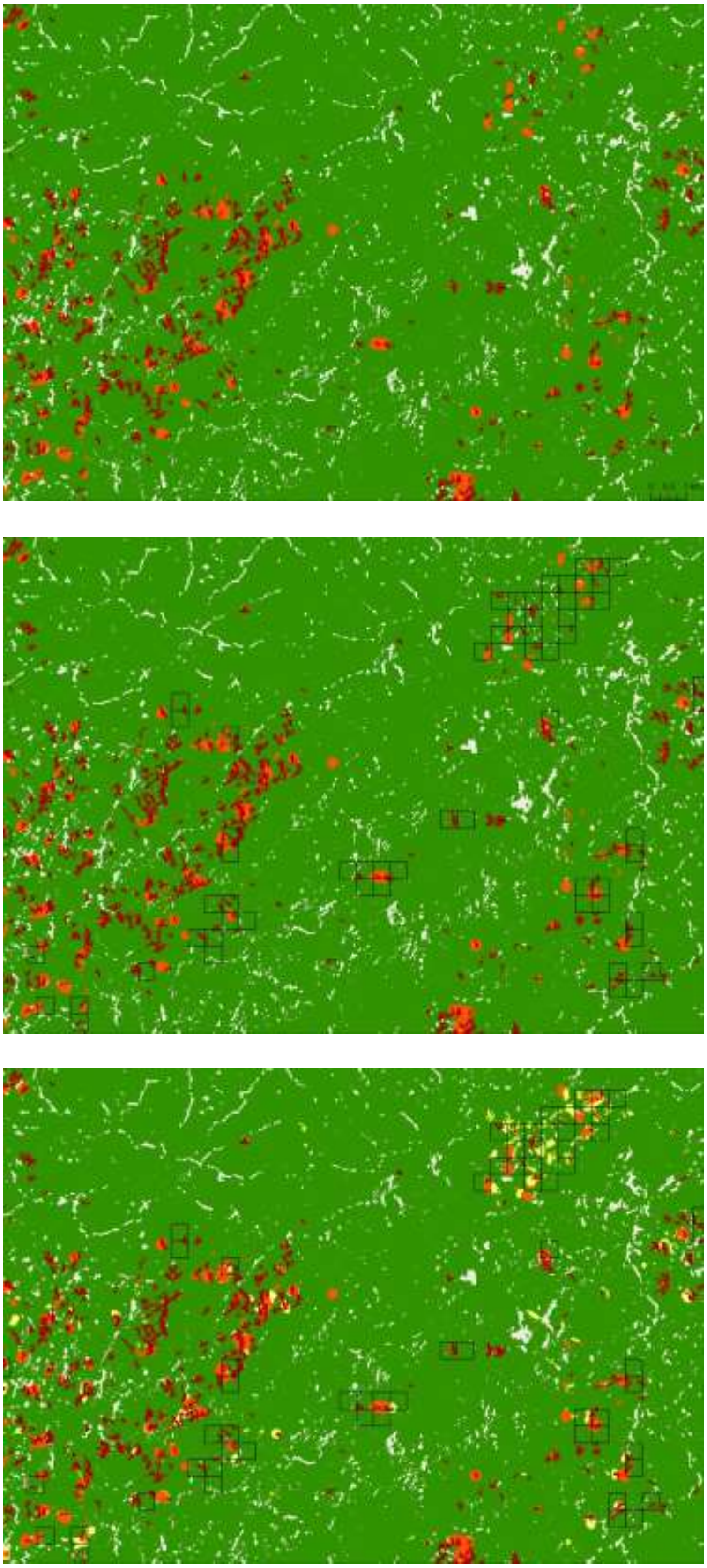

Figure 8: Deforestation and degradation monitored and deforestation predictions, Sarawak

Step 1. Deforestation and degradation at the time of prediction, June 2020

Step 2. Deforestation predictions for the following 6 months.

Step 3. Deforestation and degradation 6 months after predictions, December 2020.

Predictions 12-06-2020
Forest
Deforestation December 2015 - June 2020
Degradation December 2015 - June 2020
Deforestation June 2020 - December 2020
Degradation June 2020 - December 2020

4.3 Implementation 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 prevent or mitigate these risks as much as possible. Responses of individuals, local communities and other local stakeholders are challenging to predict, and likely vary by landscape. Potential counterproductive responses could lead to misuse of the system. One example is the leakage effect; if potential deforestation actors have information on which areas have been flagged by alerts in the EWS, they might shift their plans to other areas. Another possible outcome is social and economic instability. A response to monitoring with big data and allegations before illegal actions are even initiated, could lead to confusion and lack of understanding from local stakeholders. Moreover, due to the transparency of the EWS, differences between 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 evident in all cases. Other potential risks concerning the implementation 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. Through WWF's ESSF framework [2], WWF ensures that communities are informed about EWS in the areas and enables communities to be part of the decision-making process if they are directly or indirectly involved.

4.4 Current status of EWS pilots

As mentioned, the approach to the EWS is two-fold, so parallel to the development of the technical aspects of the EWS for Kalimantan, Sarawak, Suriname, Guyana and Gabon, processes have been initiated to ensure adequate on-the-ground activities. Hence, the pilots include setting up local collaborations, testing implementation practicalities and evaluating the success of the system as a whole.

EWS pilot plans are co-developed with local stakeholders, which include governance setup, claryfying roles of stakeholders, and deciding on meeting routines to plan investigations and interventions. Field implementation has started or is close to starting in several landscapes. Despite some delays due to, for example, COVID-19, the University of Palangkaraya and local stakeholders have done 18 field investigations in Central Kalimantan thus far. The Mid-Term Review of this pilot already shows added value, such as efficient use of patrol and gaining new information. On the 18th of February 2021 a pilot agreement among a diverse range of stakeholders was signed in Suriname for investigations and interventions. In Gabon a pilot including field work is starting soon as well. The viability and impact of EWS will be assessed after an appropiate time succeeding field interventions. Regarding potential impact, analysis for Borneo and Sumatra showed that EWS has the potention to reduce illegal

[2] *"WWF's Environmental and Social Safeguards Framework (ESSF) provides an institutional mechanism to manage the environmental and social risks of WWF's work, helps deliver better conservation outcomes, and enhances the social well-being of local communities in the places where WWF operates."* (https://www.worldwildlife.org/publications/environmental-and-social-safeguards-framework)

deforestation up to 30% once fully adopted by stakeholders, corresponding to 260 thousand ha of forest loss or 200 million tCO_2 emissions avoided.

4.5 Future geographical outlook

The 24 deforestation fronts WWF's Deforestation Fronts Report identifies the places with active deforestation in the period from 2004 and 2017, losing more than 43Mha of forest (Pacheco et al., 2021) (Figure 9). These deforestation fronts are used in setting EWS's priorities in selecting new roll-out landscapes. EWS will roll out in some of the deforestation fronts based on social and political opportunities, but only when risks associated with the program can be mitigated and fall within prespecified tolerance levels.

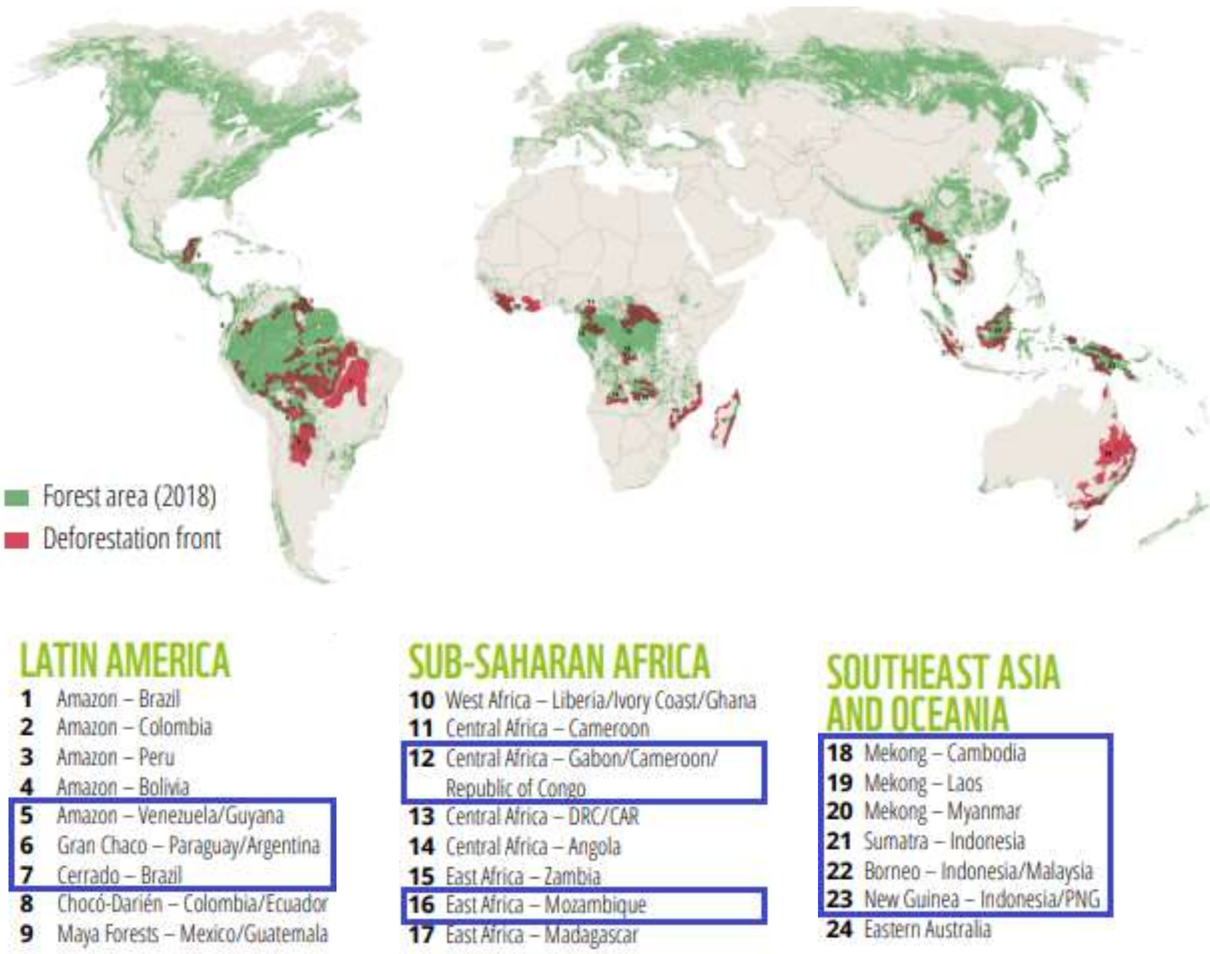

Figure 9: Worldwide forests and the 24 deforestation fronts (WWF's Deforestation Fronts Report, 2021) adapted to include blue boxes in legend around landscapes intended to scale EWS to.

4.6 Next steps on technology

The EWS programme has focussed so far on a 6-month medium-term predictive model. In the future, both a short-term predictive as well as a reactive model will be tested for feasibility as well and could complement the medium-term predictions in terms of additional possible interventions suitable for these types of predictions and timeframes. The short-term model will predict where high-risk deforestation hot zones will occur one to four weeks into the future, to support preventive measures such as rerouting of patrols. The reactive model will provide near real-time (within one to four weeks) detection of illegal deforestation activities using radar technology, to support more timely enforcement.

As the medium-term predictive model and its technological 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.

5. CONCLUSION

EWS is starting to take shape; the model is already reaching the desired accuracy, the dashboard will guide local stakeholders and decision-makers to prioritise alerts in the pilot areas and the system is embraced by local stakeholders for implementation. Collaboration with local stakeholders, tech and consultancy partners enhanced the EWS, so it is suitable for larger areas and can be adapted for more landscapes. Next steps include integration of feedback from local and national stakeholders, improving adoption of the system and further development of actionable intervention protocols. The excellent model performance, inclusive approach and solid, innovative system enables national and local governments, law enforcers and local communities to rely on the system, experience local ownership and collaboratively tackle illegal deforestation.

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