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Preventing the Trampling of Wildlife through a Heuristic Mechanism for Drone Swarm Auto-Organization in the Sierra de Huautla Reserve

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Abstract. Preventing the trampling of wildlife is a multidimensional problem that includes, among other things, a geospatial analysis of areas where the habitats of certain species of mammals in particular are found, which must cross between areas that have been isolated. A review of the literature has identified that an adequate proposal has been to build safe corridors under bridges, although the height and space of these must consider the space for a large herd. Deforestation has several causes, but wildfires and illegal tree cut, which are man-made, are the mayor. Current technology used to detect wildfires are: meteorological stations and satellite image and satellites. This last is a great option, but, from space, the fire detection is until it is large enough to be seen from orbital altitude. A drone can be used to monitor a forest looking for fire signs before the satellite observes it, but a single drone to cover a large acre surface is not optimal. A drone swarm with auto-organization capacity, equipped with atmospheric sensors that detect fire hazard conditions or even a fire in an early stage, needs to be used to optimize the area coverage. Implement a heuristic algorithm for drone swarm auto-organization applicable for wildfire alert and detection. Forest fires are a big environmental problem due they are mainly detected until they have burned some square kilometers. When these are detected at the developed stage, the fire will be difficult to contain. Some wildfires affect agricultural along as residential areas causing significant economic loses.

Keywords: Trampling of wildfire, heuristic mechanism, drone swarm auto-organization.

1 Introduction

According to Bala et al [1], prevention of trampling of wildfire, deforestation and promotion of afforestation have often been cited as strategies to slow global warming. Deforestation releases CO2 to the atmosphere, which exerts a warming influence on Earth's climate. However, biophysical effects of deforestation, which include changes in land surface albedo, evapotranspiration, and cloud cover also affect climate.

This research is presented in 4 sections. In the first section, an overview of the geographical area in Morelos where we are focusing this research, the trampling of wildlife prevention in the Mexican state of Morelos, which is very rich in natural resources. In section 2, we describe the natural resources, economic and social impacts of trampling of wildlife and forest wild fires in this region. Also, in this section we show what methods and technologies are used to detect wild trampling of wildlife and forest fires and how our research considers it. In section 3, we present the formalization of the problem and the proposed solution on how to use an autonomous, self-organized drone swarm to prevent forest wild fires. In section 4, we briefly discuss the opportunities this research represents for future applications regarding the use of self-organized drone swarm.

2 Forest Characterization in The Sierra de Huautla Reserve

Overview. In this section, the area in Morelos where this research is to be implemented, is briefly described, mainly ecosystem, as is seen in Figure 1. Morelos is located in Central region of Mexico, in the border with Puebla, State of Mexico and Guerrero.

It is conformed by 37 municipalities. The capital is Cuernavaca. On 2015 counting census, the population was 1,876,574. The state is very rich in cultures, which, co-habit with Tlahuica people in 4 native indigenous municipalities: Coatetelco, Hueyapán, Tetelcingo y Xoxocotla. A unique characteristic is that it is a 4,927 km^2 state which is composed by different ecosystems from Cold Mountain climate (similar to the ones in Sakha Republic) [2], to mountains, depressions and Forests [3]. It houses a very diverse flora and fauna as depicted in Table 1

2.1 Endemic Species in The Sierra de Huautla Reserve

The term species refers to a set of natural populations where the members that compose can reproduce each other, however, cannot reproduce with members of populations belonging to other species. The gene pool of the species maintains its integrity by biological barriers, for example, urbanization, predators, deforestation, ensuring reproductive isolation. The speciation is where a set of organisms, with a considerable number of members, are isolates geographically because the effect of people in its habitats or population ecologically of its original population, the variations that appear allow to become in a new species, this occurs when a specie has dismounted their habitat by different situations as trampling of wildlife or fire forest.

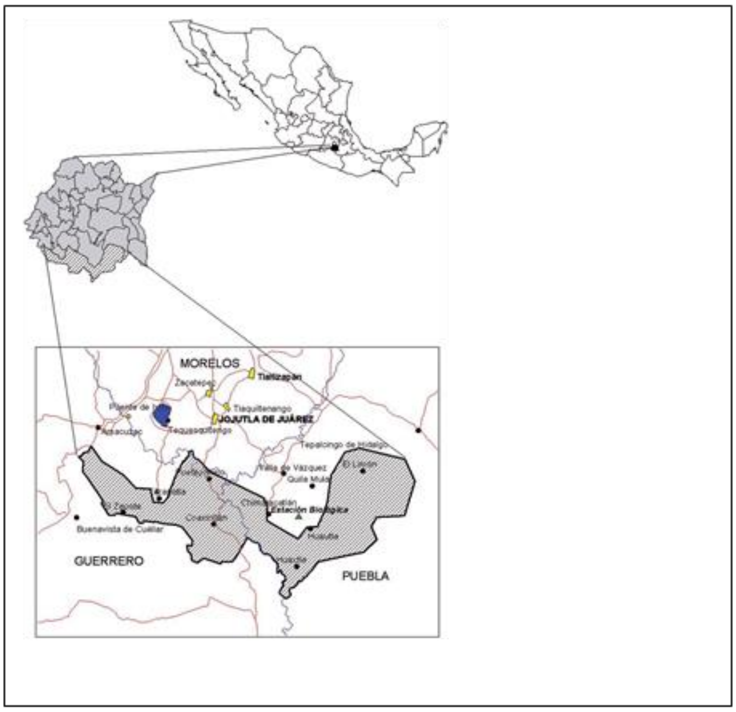


Fig. 1. The Sierra de Huautla Reserve in Mexico.

Table 1. Annual precipitation in Morelos's ecosystems.

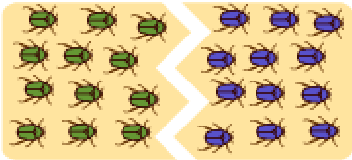
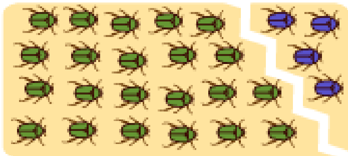
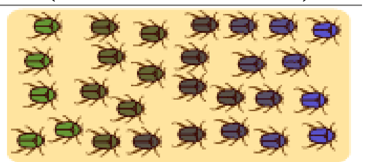
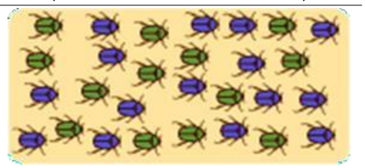
Climate Zone	Elevation (Mts)	Average Annual Precipitation (mm)	Months
Cfb	2,200	990	July - September
Cwa	1,300 - 2,200	700	July - September
BSk	1,200 - 1,500	475	August - October

During the speciation, reproductive isolation mechanisms (RAM) are introduced that prevent gene flow between populations belonging to different species, also occur the mechanisms of preggotic isolation that are those conditions of time or space that do not allow the formation of the zygote. If the mechanisms of preggotic isolation are not consolidated, interspecific mating could result, resulting in hybrid zygotes. In these cases, the postzygotic RAM, make impossible the development of the zygotes and that the hybrids achieve the adult state or they are infertile. In most cases, surviving hybrids are usually sterile.

The processes of speciation can be divided into two categories: speciation by divergence and instant speciation; Speciation by divergence refers to the fact that reproductive separation is formed gradually when a spatial or ecological barrier prevents gene flow between two sets of a population and instant or quantum speciation, the separation is established in a sudden form different kind of reptile.

There are four main models of speciation divergence shown in table 2.

Table 2. Types of speciation in an isolated population of issues in the Sierra de Huautla Reserve.

Type of speciation	Causes	Representation
Allopatric (alo = other, patric = homeland)	Geographically or ecologically separated populations.	 Allopatrinc Speciation. Source: (Caldwell & Collins, 2010)[12].
Peripatric	A population with few members separated at the end of another population with greater number of members.	 Peripatric speciation. Source: (Caldwell & Collins, 2010)
Parapatric	A population with a continuous distribution.	 Paripatric Speciation. Source: (Caldwell & Collins, 2010)
Sympatric	Within the range of the hereditary population	 Sympatric Speciation. Source: (Caldwell & Collins, 2010)

To perform the simulation with cellular automata, an endemic species that inhabits the state of Morelos, the squamous mesquite lizard was selected because it has been studied for several years by the speciation process that it presents. This species is protected by SEMARNAT, as they are threatened by the degradation of natural habitats due to urbanization, the division of spaces by the construction of motorways, intensive agriculture, grazing, burning, deforestation and tourist activities. In the state of Morelos, there is a severe impact due to the construction of Huexca Central power station. In the Sierra de Huautla Reserve, there is clandestine logging that causes depletion and contamination of water sources [4]. Poaching is pressing populations of important species.

The high incidence of forest fires reduces the opportunity for ecosystems to recover in time and form is therefore the importance of using drones that can help

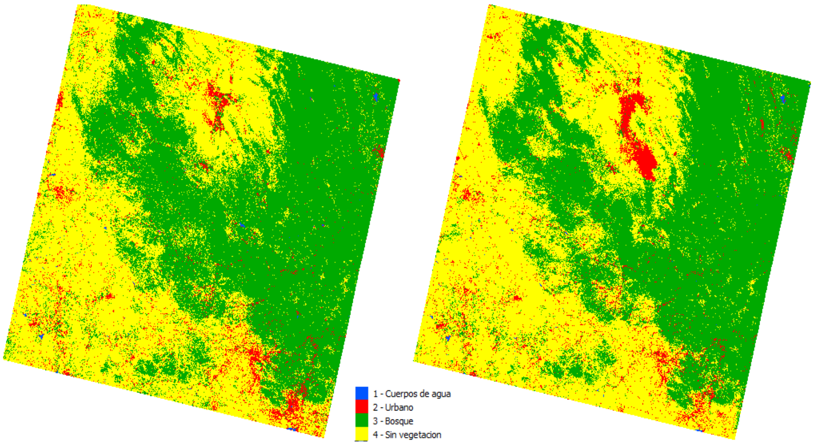


Fig. 2. Comparative map of the land use classification map of the years 2017 and 2020 in a section of Sierra de Huautla Reserve.

Fig. 3. Implementation of a proposal solution to adapt a drone to prevent trampling of wildlife and fire forest during a more widely time on Morelos' forests.

reduce this problem [5]. Considering the problem of wildlife run-over, it is necessary to establish the georeferenced accuracy of where the death situation occurs, determine the species and consider if the accident affected the ecology of any species population. In figure 2 is possible identify the reduction of habitats associated with specific species.

In figure 3, the use of a drone as part of a drone cluster can be analyzed to adequately determine the effect of wildlife runs, by specifying and validating whether a herd of a given species is attempting to migrate from one point to another in the space that makes up its habitat.

A decisive role in our research has been the implementation of an Industrial 3D printer in order to develop components of a drone cluster that allows to co-organize in order to detail searches according to the needs of the research to be carried out and to be able to diminish the effects of the fauna run over, especially in night and low visibility situations.

Table 4. Historical data of wild fires in Morelos, Mexico and its possible effect in trampling of wildlife.

Year	Quantity of fires	Burned Surface	Average Surface	Trampling of wildlife reported	Damage to the species' habitat	Reduction of population ecology
2010	1,057	18,505	17.51	2787	1.54	6.03
2011	625	10,560	16.9	2487	6.53	2.36
2012	1,153	17,216	14.93	1370	2.42	4.84
2013	842	10,704	12.71	1850	6.83	3.02
2014	697	29,316	42.06	781	6.03	2.58
2015	1,687	87,920	52.12	1362	3.79	5.31
2016	1,473	55,979	37.47	1035	3.44	5.02
2017	1,137	30,554	26.87	2069	1.02	4.86
2018	817	17,600	21.52	1124	2.88	4.56
2019	251	1,974	7.83	1980	6.78	2.60
2020	701	13,353	19.04	2997	3.97	6.21
Total Average	949	26,698	24	2493	4.29	4.77

3 Forest Wild Fires in Morelos State and Correlation with Prevent Trampling Of Wildlife

Overview. In this section, statistic data of Morelos forests wild fires that can give us an idea of the impact on the ecosystem as social and economics. Also, it's briefly described the technologies used to detect wildfires. Vegetation cover in forest ecosystems and as a consequence erosion and soil degradation. Historically, our State has seen affected by this type of casualties, the years of greatest occurrence were in the past from 1995 to 2004 and 2008, which showed a significant decrease to the year 2015, returning to present a rebound during the 2016, with a historical average of 870 annual fires between 1995 and 2020. The main causes of fires are still those related to Agricultural activities, slash and burn and the Crops, with a percentage that fluctuates between 25 and 60%. Regarding the type of ecosystem (CONAFOR 2015), the most affected is the cold temperate climate, followed by natural pasture. The smaller area report is the arid and semi-arid, as for forests there were no fires. The most common type of fire is the superficial fire. The year 2019 presented totally atypical conditions, since only Presented 252 forest fires, affecting a total area very large.

Surface recognition is a very common need like for agriculture, disaster relief operations, goods delivery, in another spatial issues. Depending on the area size, this could take a significant amount of time. For this, there's a need to use tools like a drone, but, also, this need so to have a mechanism to efficiently perform these activities and, mainly, surface recognition to optimize time. And resources depict need to coordinate the drone swarm to determine affectation in trampling of wildlife.

3.1 Case study Correlation between Fire Forest and Trampling of Wildlife

Wildfire detection and its effect on trampling of wildlife in early state case study for implementing a heuristic algorithm for drone swarm auto-organization poses some challenges:

A) Drone technology. Current drone technology is limited in capacity of taking long-range flights due battery life which is consumed in function of drone flight mainly. Adding a sensor data-logger and transmit data to a ground station represents a load to the battery life that has to be taken into account. Sensor and

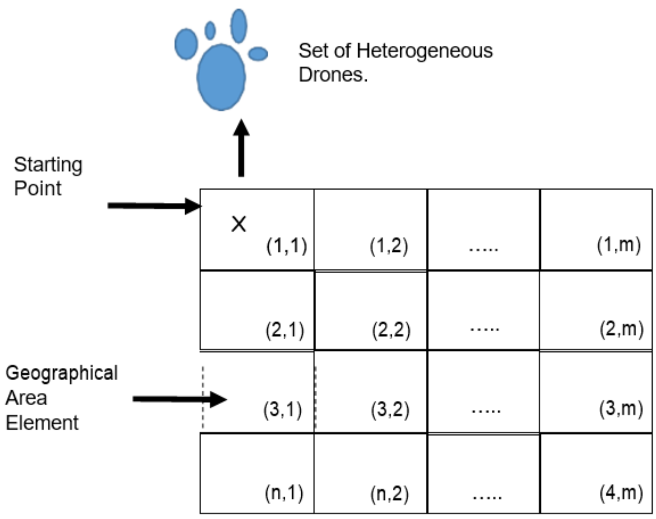


Fig. 4. Representation of the problem.

data transmission electronics does not represent a weight load in the aerial vehicle [6].

B) Radio signal. Data from the sensor data logging shall be transmitted to ground station. Due the forest geography, not all areas are covered by radio-signal. This can be solved by using some agents of the drone swarm serve as signal relay. This may represent a challenge to the auto-organization algorithm [7].

C) Altitude. Current drone technology is limited in the altitude it could reach depending on the orography where it will be implemented. This challenge is out of the scope of the auto-organization algorithm, but shall be taken into account due spherical coordinates will be used [8].

Since we're going to be working with very extensive surface of forests, these extension needs to be delimited by areas, which is the base on where the algorithm is going to define the priorities to visit by the drone swarm agents. The area to be monitored is considered in the algorithm. In the next section, it is described which are the already-known algorithms that will be referenced.

4 Formalization of the Problem

Overview. In this section, the problem we work on solving is defined and also, the drone swarm algorithm is described. We consider the problem of monitoring a large geographical area using a drone swarm to prevent forest fires which affect at many species associated with trampling of wildlife, as is possible determine in figure 4. The area to be monitored is divided into well identified sub-areas. A drone swarm is composed by a set of heterogeneous drones which are located at a starting point. Thus, the problem that we tackle is to create a schedule containing the assignment of drones to geographical sub-areas for monitoring and detecting forest fires, such that the schedule completion time is minimized.

A scheduling system model for planning the visit of drones to geographical sub-areas consists of the following elements: the geographical area, drones swarm and an objective function for scheduling.

4.1 Large Geographical Area

The geographical area is denoted by *A*. Without a loss of generality, we assume that A has a square shaped area and does not contain any obstacle. The square shape was chosen for simplicity in the model. The area *A* can be divided into finite sub-areas forming a vector $A= \{a_0, a_1, a_2, .. a_{nm}\}$ of dimension n-by-m. For convenience, we consider a_0 as the base from which drones depart and return after complete their mission. We use *Geo*(a_i) to denote the geographical position of a_i on A.

4.2 Heterogeneous Drone Swarm

The Heterogeneous Drone Swarm (HDS) can be represented by a DAG *HDS: :(D, E)*. *D* represents the set of heterogeneous drones that compose the swarm. *E* is the set of directed arcs connecting different pairs of drones, so $e\ (d_i, d_j)$ denotes a precedence that indicates that drone d_j cannot start its mission until d_i finishes its mission. For convenience, $Pred\ (d_i)$ denotes the subset of drones that directly precede d_i and $Succ\ (d_i)$ denotes the subset of drones that directly follow d_i. The entry drone is those with $|Pred\ (d_i)| = 0$ and the output drone are those with $|Succ\ (d_i)| = 0$. For simplicity, in these cases we consider the use of dummy tasks such that the dag contains only one entry and output drone. Remembering that the drones are heterogeneous, we represent the estimated flying time from the base at a_0 with EF*T*: :D × *A* → *Int*, where EF*T* (d_i, a_j) denotes the time for a drone d_i to reach a geographical sub-area a_j. For simplicity, we consider that the flying time to return to the base at a_0 is the same than the time to reach a particular area from a_0. A drone can be assigned to different missions, but it can only perform one mission at time. Thus, at time *t* we consider *avail*::*D* → [0..1], which captures the availability of each drone at time *t*. Note that the time of the mission of a particular drone is given when it is working at full availability. $W(d_i)$ denotes the time for a drone d_i to execute certain work once it reaches a geographical sub-area. $Setup(d_i)$ denotes the setup time for a drone to start a new mission. We assume that information about the flying and setup time are provided in standard time units, compatible with our drone performance measures.

4.3 Scheduling Problem

Scheduling drones to geographical areas requires the consideration of four events: (a) The time at which the drone starts its mission. (b) The time for a drone to reach a particular geographical area. (c) The time for a drone to perform certain work once it reaches its geographical area and (d) The time for a drone to return to the base. Thus, we first need to predict the time at which a particular drone departs from a_0 to perform its mission to a particular sub-area and the time in which the drone returns to the base.

1. Set the drone flying time.
2. Set the drone setup time.
3. Set the drone work time.
4. Calculate DR_u for each dron by traversing the graph from the exit node to the entry node and keep the values in L.
5. Sort the drones in L in descending order of DR_u values.
6. Create a list *LSA* with the sub-areas composing A.
7. **while** there are unvisited areas in ***LSA*** do
8. Select the first sub-area a_m from *LSA*
9. **for** each available dron d_i ($avail(d_i)=1$) in L **do**
10. Compute EDT (d_i, a_m) value.
11. Compute ERT (d_i, a_0) value.

Fig. 5. The DERT algorithm.

We must first define two mutually referential quantities. $EDT(d_i, a_m)$ is the *Estimated Departing Time* of drone d_i to a_m, it is calculated by:

$$EDT\ (d_i, a_m) = Setup(di) + max\ dj\ \in Pred(di)\{ERT(d_j, a_0)\}. \tag{1}$$

Setup(d_i) is preparation time for a drone to start a new mission. It is added to the result of the max block in Equation (3), which returns the maximum estimated returning time in which each drone in *Pred(d_i)* return to the base. This is calculated by $ERT(d_i,\ a_0)$, which denotes the *Estimated Returning Time* of drone d_i to the base located at a_0 and it is calculated by:

$$ERT\ (d_j, a_0) = EDT(d_j, a_m) + \big(2 * EFT(d_j, a_m)\big) + W(d_j\ ). \tag{2}$$

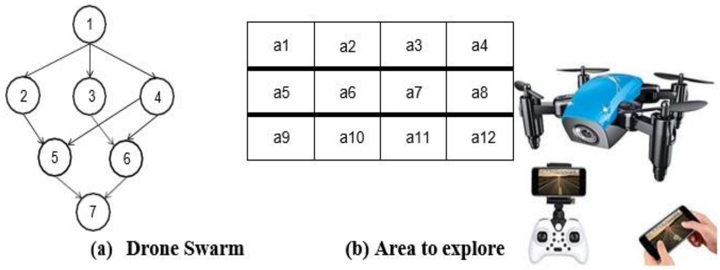
Once that all the drones have been scheduled, the estimated completion time of the schedule is determined by the estimated return time of the output drone. The estimated completion time is also known as the schedule makespan:

$$ERT(d_{output}, a_{m.\,n}). \tag{3}$$

The objective function for drone scheduling aims to create a schedule containing the assignment of drones to geographical sub-areas such that its makespan is minimized.

4.4 DERT Algorithm

The DERT algorithm is based on the well-known list scheduling approach. Our interest in this approach is to explore low computational complexity strategies and apply them to prevent and combat forest fires with the use of drones. Thus, the DERT Algorithm basically consist of two phases: The *drone prioritization phase* in which a priority rank assignment is set to each drone. The *geographical sub-area assignation phase* where each drone is assigned to that geographical sub-area which optimizes a predefined cost function. The DERT algorithm is shown in Figure 5.



Dron	a1	a2	a3	a4	a5	a6	a7	a8	a9	a10	a11	12
1	7	3	9	4	9	4	3	3	1	2	9	9
2	4	7	18	3	2	7	7	2	7	8	7	5
3	8	2	19	4	7	1	2	8	4	4	4	1
4	9	9	17	3	2	7	9	1	2	2	3	5
5	4	8	10	5	9	9	8	8	9	1	4	9
6	5	5	9	8	2	3	5	4	5	8	8	4
7	2	3	11	2	3	3	3	7	3	2	7	3
8	7	5	14	4	7	5	5	5	5	3	3	4
9	3	4	20	3	4	4	4	4	2	4	1	4
10	1	5	2	7	2	5	5	5	10	7	3	2

Fig. 6. Proposed model for the location, monitoring, management and geolocation of wildlife runs to determine the effects on their herds and therefore on the ecology of their populations.

4.5 Drone Prioritization Phase

We use *DRu(di)*, an upward rank defined as the length of the critical path from drone d_i to the output drone. *DRu(di)* is calculated recursively as:

$$DRu(d_i) = \text{avg}\,(FT_i)+max\ vj \in Succ(vi)\ (DRu(v_j)), \quad (4)$$

where avg(FT_i) is the average of the visit time for a drone d_i across all sub-areas.

$$avg\big(Ft(di)\big) = \sum\nolimits_{k=0}^{nm} \frac{(d_i a_k)}{nm}.$$

5 Sub-area Assignation Phase

The DERT algorithm considers that a drone can be assigned to several missions, but it only can perform once at time. A mission involves to depart from the base a_0 to an assigned area a_m, perform a work once it reaches a_m and return to a_0. In our case, the work that a drone performs at a particular area is to monitor. The assignation phase

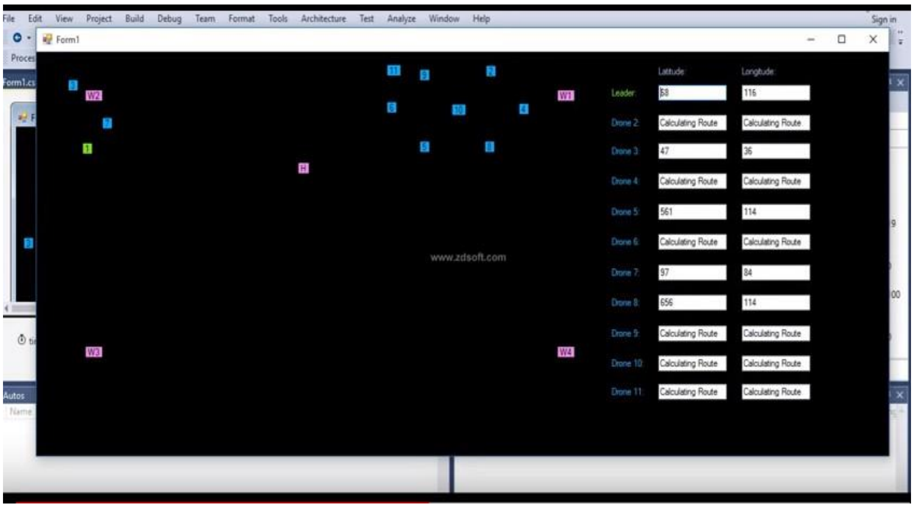


Fig. 7. Simulation software of our cluster of drones to prevent trampling of wildlife.

where a drone is assigned to a geographical sub-area offering the minimum estimated returning time, takes *O(d x e)* time complexity for *d* drones a *e* precedence's.

5.1 Example of Use in a Real Scenario

Using our drone cluster and the mobile application for its monitoring, it was possible to determine the effectiveness index associated with the evaluation of a given region, and to determine where wild fauna runs over, as can be seen in figure 6 and through the proposed model to determine the respective affectation to the ecology of populations of a given species.

By properly utilizing our mobile device to synchronize control of tasks associated with our drone cluster, we can properly identify the ideal wildlife management organization and achieve a predictive model that will reduce the number of wildlife strikes.

5.2 Simulation

This research still needs to be complemented with simulation and testing prior to implement it in a real environment. Beside the engineering challenges of a physical drone swarm, the developed algorithm described in section 3 will be simulated for fine tuning and validation. For this, the forest and wildfires will be modeled to replicate as close as possible the ecosystem were these drones will eventually be flying.

Using our intelligent application, we can visualize even in a night scenario if there is any wildlife run over and how these collateral damages associated with the decline of a particular species can be diminished.

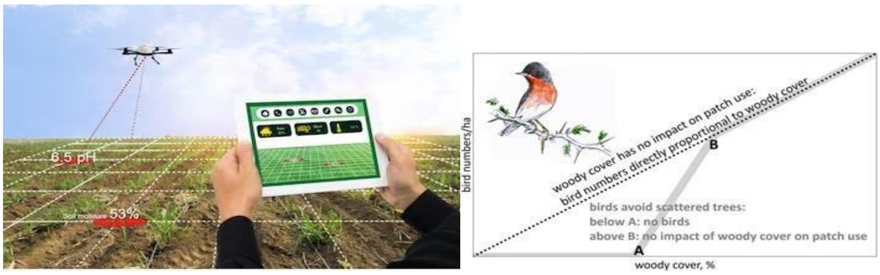


Fig. 8. A wood portion with illegal tree cutting identified by a machine learning model to determine the affection in a group of arboreal bird species.

6 Future Research

Overview. In this section, the future work for the drone swarm algorithm is described, the next challenges to be taken and opportunities, as Illegal tree-cutting detection in figure 8. It is important to adequately determine the amount of tree loss associated with illegal logging, in order to subsequently establish a level of actual impact associated with the future effects of specific changes and over time on the ecology of populations.

All around the world, illegal tree cutting is a big problem with several causes and big consequences to the global ecosystem as mentioned in the introduction of this research. This comes to account due one of the next works involving the presented heuristic algorithm for drone swarm auto-organization is to monitor forests to detect illegal tree cutting. Not only surveying forests with the flying unmanned aerial vehicles (UAVs), but equip this swarm agents with image recognition based on a machine learning model to be developed. The authors of this chapter are now starting to get involved on this endeavor.

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