



Spatiotemporal risk forecasting to improve locust management

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Locusts are among the most feared agricultural pests. Spatiotemporal forecasting is a key process in their management. The present review aims to 1) set a common language on the subject, 2) evaluate the current methodologies, and 3) identify opportunities to improve forecasting tools. Forecasts can be used to provide reliable predictions on locust presence, reproduction events, gregarization areas, population outbreaks, and potential impacts on agriculture. Statistical approaches are used for the first four objectives, whereas mechanistic approaches are used for the latter. We advocate 1) to build reliable and reproducible spatiotemporal forecasting systems for the impacts on agriculture, 2) to turn scientific studies into operational forecasting systems, and 3) to evaluate the performance of these systems.

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Current Opinion in Insect Science 2023, 56:101024

This review comes from a themed issue on **Ecology**

Edited by **Kyle Haynes, Derek Johnson and Andrew Liebhold**

Available online 21 March 2023

<https://doi.org/10.1016/j.cois.2023.101024>

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Introduction

Locusts are among the most feared agricultural pests across the world. Their phase polyphenism allows them to go from a solitary phase at low density to a swarming gregarious phase at high density [1]. This extreme form of phenotypic plasticity confers them the capacity to quickly outbreak through this phase change called ‘gregarization’. The understanding of their ecology as well as finding new ways to control them have been the subject of many scientific studies (see reviews by [2–4]).

Despite this knowledge, locusts continue to cause important damage to agriculture in the 21st century. More than 400 million US\$ were spent to stop *Schistocerca gregaria* in Africa between 2003 and 2005 [5] and several hundred million US\$ in Eastern Africa and Southwest Asia between 2019 and 2021 [6]. In 2013–2015, a 37 million US\$ effort was necessary to control a large outbreak of *Locusta migratoria* in Madagascar [7]. Central Asia was strongly impacted in 2014 by *L. migratoria* and two other locust species, *Dociostaurus maroccanus* and *Calliptamus italicus*. Australia is also regularly affected by *Chortoicetes terminifera*, which displayed a large outbreak in 2010 costing 50 million US\$ [8]. Another example was *Schistocerca cancellata* that exhibited an outbreak in Argentina, Bolivia, and Paraguay from 2015 to 2020 [9].

A preventive approach to control locusts was proposed as early as the 1930s after the discovery by Uvarov [10] of phase polyphenism. There have been debates about when to initiate locust prevention measures [11,12], as well as whether to call it ‘proaction’ after gregarization occurs [13]. Nonetheless, most antilocus management systems nowadays appear to favor proactive or preventive actions taken before swarms have an impact on agriculture [4]. Such preventive management needs a monitoring system triggering early warnings to deploy a control response to onsets of outbreaks. In this context, spatiotemporal forecasts are useful at different levels. Forecasts help to orientate field teams and improve the efficiency of the monitoring system. Forecasts are also necessary to justify the control response when outbreaks happen. The present review aims to 1) set the bases of a common language about spatiotemporal locust risk forecasting, 2) evaluate the current methodologies at different scales of forecasting, and 3) identify opportunities and challenges of scientific research to develop improved forecasting tools for the management of locusts.

Definitions and objectives of spatiotemporal locust risk forecasting

To improve monitoring, proactive action implementation, and management evaluation from the knowledge gained from the forecast, we need to have some common terminology definitions. The term ‘risk’ is used throughout locust literature but with rare definitions given. We consider the definition of the International Standardization Organization of risk as the ‘effect of uncertainty on objectives’.

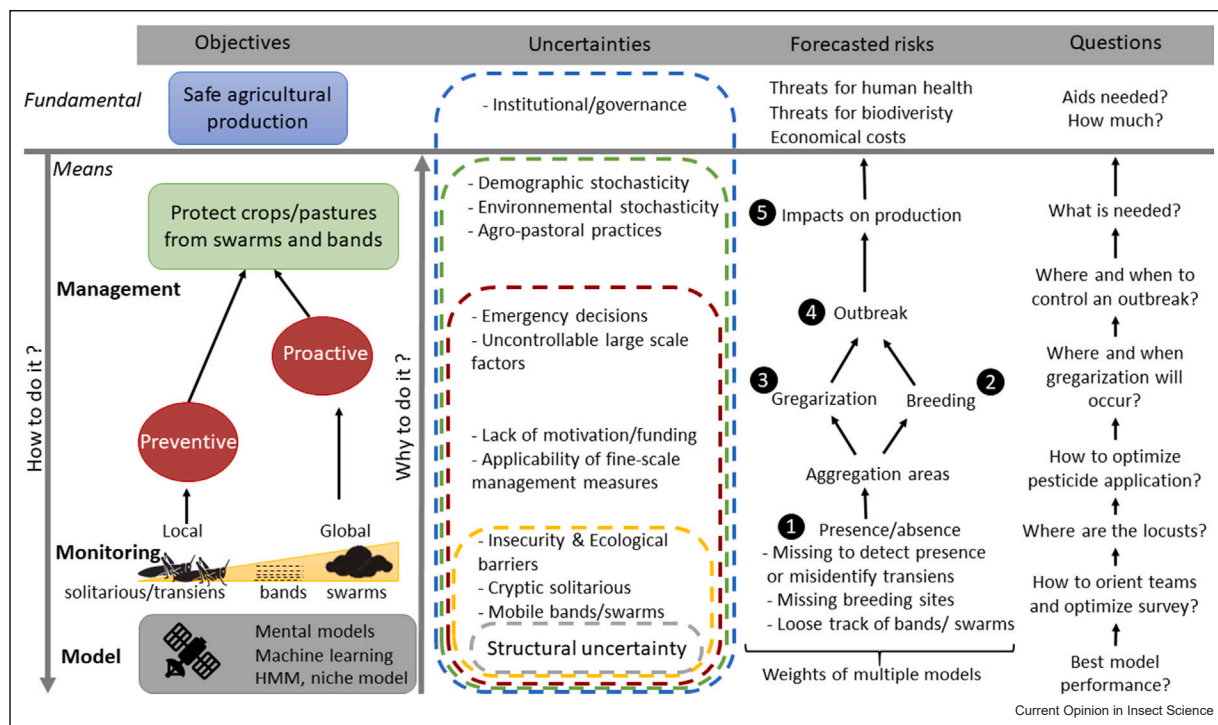
This definition supposes to have identified the ‘*objectives*’ at stake. The main and fundamental objective of locust management is to maintain safe agricultural production (Figure 1). To reach this main goal, intermediate ‘*means*’ objectives emerge, at different stage of the management process, ranging from (early) prevention strategies to (late-stage) crop protection measures (described in [4]). In a preventive strategy context, the means objectives are to monitor different levels of locust population development to avoid missing the onset of an outbreak. In a proactive context, the means objective is to monitor bands and swarms’ development before they reach cultivated lands. The differences between fundamental and means objectives have been defined in adaptive management [14].

The standard definition of risk also stresses the importance of *uncertainty*, ultimately positioned as the main source of the risk. Uncertainty may come from an unpredictable event or a predictable but unexpected or unforeseen event [15]. In locust management, most

outbreaks could be predicted by environmental drivers of population development. However, there are different uncertainties regarding the occurrence of the predictable events due to unknowns on the situation in the field, including the capacity of the management system to respond and the future of climatic conditions (Figure 1).

This standard definition of risk with objectives and uncertainties leads naturally to *forecast* events related to locust risks under different sources of uncertainties. In this context, forecasts are statements that give probabilities of particular events to happen. Locust risk forecasting hence needs to have defined the objective at stake and the sources of uncertainty that generate the risk. Figure 1 summarizes the different levels of mean objectives, the corresponding uncertainties, and forecasted risks. The hierarchical levels of mean objectives in Figure 1 correspond to different means to reach the fundamental objective and avoid the associated risks. The 5 different forecasting events highlighted in Figure 1

Figure 1



Forecasting locust-related risks at different spatiotemporal scales and governance levels as a means to fulfill a main goal: maintain safe agriculture. This goal is the fundamental objective, it relies on decision-makers and stakeholders’ values. It answers the question ‘why is it important?’, while the means objectives answer the question ‘how to get there?’. Those provide the tasks and forecasting tools necessary to reach the main goal from the bottom to the top (model, monitoring, and management). The figure presents those risks as the conjunction between objectives and uncertainties. Risk forecasting provides decision-makers answers to the underlying monitoring and management questions regarding the strategies that could be taken. The colors correspond to different parts of the system: blue for governance issues, green for the agroecological system, red for the management, yellow for the specific surveys in the management system, and gray for the models. The uncertainties of upper levels are affecting the more precise mean objectives (hence the overlapping boxes). The risks result from the uncertainties’ effect on the objectives. The forecasts attempt to avoid the corresponding risks. Five specific forecasting events are highlighted with black circles: 1 locust presence, 2 locust breeding, 3 gregarization areas, 4 population outbreaks, and 5 impacts on agriculture. Terms were defined and the illustration was inspired by [14].

are locust presence, reproduction events, gregarization areas, population outbreaks, and potential impacts on agriculture. In the following section, we review the current methodologies for forecasting each of these events.

Current methodologies at different scales of forecasting

Forecasting locust presence

Forecasting locust presence at a small spatial scale (≤ 1 km) and under a short-to-medium time horizon (≤ 1 month) to orient field teams of the preventive management system was the objective of the work of Piou et al. [16]. They used the normalized difference vegetation index (NDVI) from remote sensing (RS) to correlate ground survey observations of *Schistocerca gregaria* presence in remission periods to vegetation dynamics and spatial structure. In Piou et al. [17], the approach was extended to soil moisture estimated also from RS and using machine learning (ML) algorithms. These studies showed that an increase in vegetation 1–2 months before or an increase in surface soil moisture 2–3 months before a survey increases the chances to observe desert locusts. These statistical works can be used to develop dynamic operational systems that map the probability of the presence of locusts. This was developed operationally for desert locust with a mapping system updating every 16 days to orient the field teams of Morocco [18].

Forecasting reproduction events

Tratalos et al. [19] showed that forecasting reproduction sites of desert locust at a scale of a few kilometers was hardly possible with NDVI. However, more recent works using ML managed to link reproduction sites and soil moisture from RS. Using Random Forests, Gomez et al. [20] showed that breeding sites of desert locust could be forecasted with a surface soil moisture above $0.07 \text{ m}^3/\text{m}^3$ for more than 6 days. Further, Gomez et al. [21] explored different combinations of variables to forecast breeding sites and found that medium soil temperature, high root-zone soil moisture, and high NDVI best explained breeding observations. Kimathi et al. [22] proposed, with a presence-only approach used in species distribution modeling, static maps of the probability of desert locust breeding depending on climatic and soil variables. Static maps of reproduction probability were also the results of spatial smoothing kernels over Mauritania and Morocco [23] and Tchad [24]. Combining static information and vegetation conditions, Klein et al. [25] used a multiscale approach integrating high spatial-resolution RS data and ecological niche modeling techniques to create breeding suitability maps of *Calliptamus italicus*, *Dociostaurus maroccanus*, and *S. gregaria* at the spatial scale of large districts or river basins.

The static maps have been used by management systems to orient field campaigns in search of breeding grounds for decades (e.g. [26]). However, operational dynamical applications integrating locust demography are still to be developed and evaluated. These should improve preventive management and particularly of diapausing locust species such as *C. italicus* or *D. maroccanus*.

Forecasting gregarization areas

In preventive management, forecasting is used to identify the gregarization sites as early as possible [4]. Veran et al. [27] developed a hidden Markov model (HMM in Figure 1) to estimate the transition probability that Australian Plague locusts, *Chortoicetes terminifera*, switch from low densities to gregarious densities. Such a hybrid method, lying between statistical and mechanistic models, allowed the disentanglement of the gregarization process from the observation processes that create uncertainty in individual detection and phase identification. Sun et al. [28], attempting to forecast desert locust hopper bands, used ML and sliding temporal windows of NDVI and soil moisture. Lawton et al. [29] used hierarchical generalized additive models to explore the relationships between temporal variations of NDVI and the presence of gregarious hoppers of *S. gregaria* and *C. terminifera*. They showed that both species respond to spatial hierarchy where regional dynamics influence the local probabilities to observe outbreaking locust populations. However, preceding vegetation growth was shown to shape the outbreaks of desert locust sooner than it shapes the Australian ones, as *S. gregaria* lives in a more arid climate, with faster vegetation growth following rainfall.

Forecasting population outbreaks

With the creation of large datasets of survey points, recent studies use advanced statistical approaches that are suitable for opportunistic and heterogeneous data collected at large scale. Some studies fit species distribution models to presence-only data to examine how likely climate change will cause shifts in locust ecological niches and will trigger outbreaks in new areas [30–32]. Ecological niche modeling was used to identify areas of potential outbreaks for several species of locusts and grasshoppers [33–36]. Checke et al. [37] showed with Ornstein-Uhlenbeck state-space testing and convergent cross-mapping that oceanic oscillations provoked by the decadal solar cycles are likely to drive abundance peaks of the desert locust and the oriental migratory locust. This study revealed that monitoring distal factors such as sunspot cycles and large-scale weather patterns may help to anticipate an outbreak.

All these studies are very promising for the implementation of operational tools. The Australian Plague Locust Commission uses a geographic information system (GIS) combining field and RS data to forecast outbreaks and distribution [38,39]. However, operational dynamical forecasting systems to map gregarization sites with a few weeks or months of anticipation are lacking for other parts of the world.

Forecasting impacts on agriculture

Some tools using field surveys, meteorological, and RS information have been designed for real-time and remote transmission of pest impacts in agricultural areas and to forecast the level of damage [38,40]. The integrated pest management models of [41–44] simulated the dynamics of *Oedaleus senegalensis* with several predators and plants, including a cost/benefit analysis of different treatments for agriculture, such as the biocontrol agent *Metarhizium anisopliae*. Cressman [45] or Pedgley [46] described the process of preparing desert locust forecasts. The FAO warning system from the Desert Locust Information Service (DLIS) provides national-level threat to crop forecasting [47]. These forecasts are based on a GIS that integrates historical and contemporary data on desert locust populations, along with observations or putative ongoing events of reproduction, migration, and gregarization and various meteorological and RS data as environmental drivers [48,49]. Many of the parts used in the building of the forecasts are coming out of scientific studies such as development models [50,51]. Recent attempts of forecasting swarms' movements [52–54] could also be used. However, scientific studies describing a reproducible process to create spatiotemporal forecasts of impacts on agriculture are lacking and forecasts may be considered as much an art than a science [45]. There is also a clear lack of systematic evaluation of forecasting accuracy at the level of impact on agriculture.

Opportunities and challenges of locust forecasting

Current methodological limitations

Many statistical tools and RS studies helped understand and map locust distribution (reviews by [55,56]). However, there is a clear need 1) to make more reliable and reproducible spatiotemporal forecasting systems for the impacts on agriculture, 2) to turn scientific studies on forecasts of means objectives at short-to-large time horizons into operational forecasting systems to orientate surveys for many locust species, and 3) to evaluate the performance of all these decision-support systems through iterative processes of learning by doing.

Before the surge of statistical models, most studies trying to predict locust outbreaks relied on deductive demographic models describing locust population

dynamics within agroecosystems under different management scenarios [11,41,42,57]. These models provided rules of thumb for managers, such as maintaining viable populations of predators along with applying treatments [42]. Yet, those models were often calibrated and validated on small datasets.

On the contrary, with the compilation of large datasets and the use of ML, nowadays, modelers tend to forget about the population dynamics processes and focus on prediction errors. Hence, two challenges need to be addressed in the complexity of locust outbreaks. First, scientists have to understand how time-lagged effects of weather and hierarchical effects of habitats can drive migration, concentration, multiplication, and gregarization of different locust species [29,58,59]. Second, they need to assess how these processes respond to management actions [27,60,61] to determine which of the risk factors are the key levers for effective management. The use of uncertainty and sensitivity analyses in models may help in this second challenge.

A further limitation currently overlooked by modelers is the data quality within the large datasets. As good forecasting is impossible without good ground survey data, training and awareness of the data collectors need to be maintained through time and particularly in recession periods [61]. The sampling design and data heterogeneity are rarely considered. Ultimately, the rise of HMM (e.g. [27]) may be the solution to these challenges.

As new statistical tools are being developed, validation with a part of the dataset is a common technique in recent studies (e.g. [17,20]). However, there is a clear need to analyze forecasts made for decades and evaluate in the field the most recent ones. Rainey [62] identified early that there are higher chances of successful forecasts in changes in the spatial distribution of locusts than in changes in population size and density. Betts [63], in a rare evaluation of DLIS forecasts between 1961 and 1965, found that low-probability forecasts are the least reliable. Nevertheless, further evaluation studies should be conducted to improve the systems and eventually confirm that forecasting experts need to have holistic knowledge more than big computers and artificial intelligence [48].

Future of locust forecasting

With constant improvements in RS and the consideration of other locust species than the three main ones (as advocated by [25]), the field of spatiotemporal locust risk forecasting is likely to improve greatly in the coming years. This is particularly important in the context of changing climate and the constant need to increase the efficiency of all preventive systems.

Pitfalls of giving too much weight to a single approach or ‘black boxes’ of ML should be avoided. Learning from meteorological forecasting systems and other branches of ecology that use decision-support systems (e.g. [64,65]) should be encouraged. Locust forecasting would also need to evaluate the risks of using citizen or ‘less-trained officers’ data that are proposed with the emergence of smartphones and artificial intelligence [53]. Well-trained locust officers should not be replaced by machines. We believe that locust ecology and human monitoring efforts should stay the central part of forecasting systems. As such, the methodological consideration of specific plant–insect interactions that exist for most locust species [66] should improve greatly the accuracy of forecasts. Ultimately, locust risk forecasts shall also consider the impacts on biodiversity, which would complement the efforts of antilocus management to evaluate the treatment impacts a posteriori [67].

Data Availability

No data were used for the research described in the article.

Acknowledgements

We wish to thank the participants of the symposium on ‘forecasting locust risks’ organized by C. Piou during the 13th International Conference of Orthopterology in Agadir in March 2019: Ted Deveson, Keith Cressman, Robert A. Cheke, Mohammed F. Smiej, Eduardo Trumper, and Jørgen Aagaard Axelsen. Their inputs and discussion gave a good basis for this review. This work was funded by ANR-JCJC (Agence Nationale de la Recherche, Programme Jeunes Chercheuses Jeunes Chercheurs, France) under the PEPPER project (ANR-18-CE32-0010-01). We thank two anonymous reviewers for their constructive comments on an earlier version of this paper.

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