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Cyril Piou, Lucile Marescot

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Cyril Piou[1,2] and Lucile Marescot[1,2]

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.

Addresses
[1] CIRAD, UMR CBGP, Montpellier, France
[2] CBGP, INRAE, IRD, CIRAD, Institut Agro Montpellier, Montpellier University, Montpellier, France

Corresponding author: Piou, Cyril (Cyril.piou@cirad.fr)

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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 solitarious 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 antilocust 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

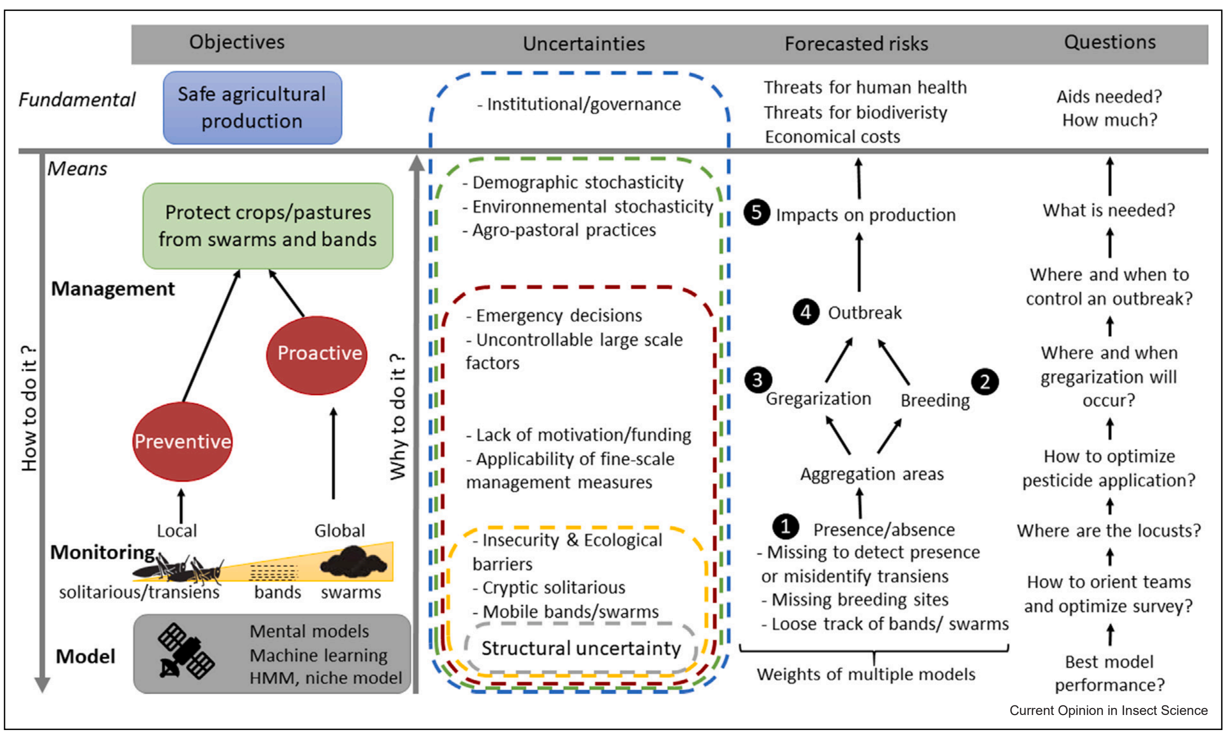
To improve monitoring, proactive action implementation, and management evaluation from the knowledge gained from the forecast, we need to have some common terminology definitions. The term 'risk' is used throughout locust literature but with rare definitions given. We consider the definition of the International 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 are locust presence, reproduction events, gregarization areas, population outbreaks, and potential impacts on

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].

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 m^3/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 hierarchal 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 antilocust management to evaluate the treatment impacts a posteriori [67].

Data Availability

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

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References and recommended reading

Papers of particular interest, published within the period of review, have been highlighted as:

- • of special interest
- •• of outstanding interest

1. Sword GA, Lecoq M, Simpson SJ: **Phase polyphenism and preventative locust management**. *J Insect Physiol* 2010, **56**:949-957.
2. Pener MP, Simpson SJ: **Locust phase polyphenism: an update**. *Adv Insect Physiol* 2009, **36**:1-272.
3. Cullen DA, Cease AJ, Latchininsky AV, Ayali A, Berry K, Buhl J, de Keyser R, Foquet B, Hadrich JC, Matheson T, *et al*.: **From molecules to management: mechanisms and consequences of locust phase polyphenism**. *Adv Insect Physiol* 2017, **53**:167-285.
4. Zhang L, Lecoq M, Latchininsky A, Hunter DM: **Locust and grasshopper management**. *Annu Rev Entomol* 2019, **64**:15-34.
5. Brader L, Djibo H, Faye FG, Ghaout S, Lazar M, Luzietoso PN, Ould Babah MA: **Towards a more effective response to Desert locusts and their impacts on food security, livelihood and poverty**. Multilateral Evaluation of the 2003–05 Desert Locust Campaign. FAO; 2006.
6. FAO: **Desert Locust Upsurge – Progress Report on the Response in the Greater Horn of Africa and Yemen, September–December 2021**. FAO; 2022, https://doi.org/10.4060/cc0175en
7. FAO: **Response to the Locust Plague in Madagascar Campaign 2014/15 FINAL REPORT September 2014 – August 2015**. FAO; 2016, ⟨https://www.fao.org/3/bs164e/bs164e.pdf⟩.
8. Millist N, Abdalla A: **Benefit–cost Analysis of Australian Plague Locust Control Operations for 2010–11**. ABARES report prepared for the Australian Plague Locust Commission; 2011, ⟨https://www.agriculture.gov.au/sites/default/files/sitecollectiondocuments/animal-plant/aplc/research-papers/locust-control-11.pdf⟩.
9. Trumper EV, Cease AJ, Cigliano MM, Copa Bazán F, Lange CE, Medina HE, Overson RP, Therville C, Pocco ME, Piou C, *et al*.: **A review of the biology, ecology, and management of the South American Locust, *Schistocerca cancellata* (Serville, 1838), and future prospects**. *Agronomy* 2022, **12**:135.
10. Uvarov BP: **A revision of the genus *Locusta* L. (=Pachytylus, Fieb.), with a new theory as to the periodicity and migrations of Locusts**. *Bull Entomol Res* 1921, **12**:135-163.
11. Magor JI, Lecoq M, Hunter DM: **Preventive control and Desert locust plagues**. *Crop Prot* 2008, **27**:1527-1533.
12. Symmons P: **A critique of "Preventive control and Desert locust plagues"**. *Crop Prot* 2009, **28**:905-907.
13. Showler AT, Ould Babah Ebbe MA, Lecoq M, Maeno KO: **Early intervention against Desert locusts: current proactive approach and the prospect of sustainable outbreak prevention**. *Agronomy* 2021, **11**:312.
14. Irwin BJ, Conroy MJ: **Consideration of reference points for the management of renewable resources under an adaptive management paradigm**. *Environ Conserv* 2013, **40**:302-309.
15. Makridakis S, Williams T, Kirkham R, Papadaki M: **Forecasting, uncertainty and risk management**. *Int J Forecast* 2019, **35**:641-643.
16. Piou C, Lebourgeois V, Benahi AS, Bonnal V, Jaavar MEH, Lecoq M, Vassal J-M: **Coupling historical prospection data and a remotely-sensed vegetation index for the preventative control of Desert locusts**. *Basic Appl Ecol* 2013, **14**:593-604.
17. •• Piou C, Gay P-E, Benahi AS, Babah Ebbe MAO, Chihrane J, Ghaout S, Cisse S, Diakite F, Lazar M, Cressman K, *et al*.: **Soil moisture from remote sensing to forecast desert locust presence**. *J Appl Ecol* 2019, **56**:966-975.

Using generalized linear models, the authors analysed the temporal lags between observation of presence/absence of desert locust during remission times in Western Africa and RS indicators of vegetation, soil moisture, rainfall, and land surface temperature. They demonstrated that following soil moisture allowed a gain of 3 weeks in timing compared to vegetation. They used random forest to illustrate how forecasting errors can be reduced by the combination of several RS indicators.

18. Smiej M.F., Layelmam M., Atillah A., Piou C., Ghaout S.: **Forecasts of desert locust presence in Morocco coupling remote sensing imagery and field surveys**, in *Proceedings of the 13th International Congress of Orthopterology*. Edited by Orthopterist Society, Agadir. 2019.
19. Tratalos JA, Cheke RA: **Can NDVI GAC imagery be used to monitor desert locust breeding areas?** *J Arid Environ* 2006, **64**:342-356.
20. Gómez D, Salvador P, Sanz J, Casanova C, Taratiel D, Casanova JL: **Machine learning approach to locate desert locust breeding areas based on ESA CCI soil moisture**. *J Appl Remote Sens* 2018, **12**:036011.
21. Gómez D, Salvador P, Sanz J, Casanova C, Taratiel D, Casanova JL: **Desert locust detection using Earth observation satellite data in Mauritania**. *J Arid Environ* 2019, **164**:29-37.
22. Kimathi E, Tonnang HEZ, Subramanian S, Cressman K, Abdel-Rahman EM, Tesfayohannes M, Niassy S, Torto B, Dubois T, Tanga CM, *et al*.: **Prediction of breeding regions for the desert locust *Schistocerca gregaria* in East Africa**. *Sci Rep* 2020, **10**:11937.
23. Piou C, Jaavar Bacar MEH, Babah Ebbe MAO, Chihrane J, Ghaout S, Cisse S, Lecoq M, Ben Halima T: **Mapping the spatiotemporal distributions of the Desert Locust in Mauritania and Morocco to improve preventive management**. *Basic Appl Ecol* 2017, **25**:37-47.

24. Kayalto M, Idrissi Hassani M, Lecoq M, Gay P-E, Piou C: **Cartographie des zones de reproduction et de grégarisation du criquet pèlerin au Tchad**. *Cah Agric* 2020, **29**:14.

25. Klein I, van der Woude S, Schwarzenbacher F, Muratova N, Slagter
• B, Malakhov D, Oppelt N, Kuenzer C: **Predicting suitable breeding areas for different locust species – a multi-scale approach accounting for environmental conditions and current land cover situation**. *Int J Appl Earth Obs Geoinf* 2022, **107**:102672.

Using a fused multiscale approach to model habitat suitability, the authors analysed how high spatial resolution RS data can enable dynamical mapping of locust breeding habitats of three locust species. They showed that high resolution imagery allows to account for current vegetation and land management situations.

26. Popov GB: **Atlas des Aires de Reproduction du Criquet pèlerin/ Atlas of Desert Locust Breeding Habitats**. FAO; 1997.

27. Veran S, Simpson SJ, Sword GA, Deveson E, Piry S, Hines JE,
•• Berthier K: **Modeling spatiotemporal dynamics of outbreaking species: influence of environment and migration in a locust**. *Ecology* 2015, **96**:737-748.

Using a multistate dynamic occupancy model formulated in a HMM framework the authors unravel the ecological processes explaining large-scale changes in the Australian plague locust distribution while accounting for field errors in the identification of phase. They found that variation in the gregarization probability was mostly explained by rainfall and land cover, with a quicker and steadier response to rains in desert habitats than in agricultural landscapes. This framework is promising for the forecast of locust outbreaks as it bridges the gap between process-driven models which often lack empirical support and data-driven models which often lack causality in the swarming mechanisms.

28. Sun R, Huang W, Dong Y, Zhao L, Zhang B, Ma H, Geng Y, Ruan C,
• Xing N, Chen X, *et al*.: **Dynamic forecast of Desert Locust presence using machine learning with a multivariate time lag sliding window technique**. *Remote Sens* 2022, **14**:747.

The authors used ML algorithm to forecast breeding areas of desert locust. They coupled historical observations of hoppers from ground survey with remote-sensing time series. The model with the greatest accuracy could determine which time-lags in the most important predictors maximize the probability to observe emergence of hopper bands in breeding sites.

29. Lawton D, Scarth P, Deveson E, Piou C, Spessa A, Waters C,
• Cease AJ: **Seeing the locust in the swarm: accounting for spatiotemporal hierarchy improves ecological models of insect populations**. *Ecography* 2022, **2022**:e05763.

Using hierarchical general additive models, they investigated the role of vegetation patch dynamics on the outbreak risk of desert locusts and Australian plague locusts in heterogeneous landscapes at three nested scales: the land unit, the geographic region, and the species range. They demonstrate that the two species' ecology follows the resource pulse paradigm, which states that primary productivity and locust response (migration and population growth) are driven by variable regional rainfall events.

30. Guan JY, Li MY, Ju XF, Lin J, Wu JG, Zheng JH: **The potential habitat of desert locusts is contracting: predictions under climate change scenarios**. *Peerj* 2021, **9**:e12311.

31. Humphreys JM, Srygley RB, Branson DH: **Geographic variation in**
• **migratory grasshopper recruitment under projected climate change**. *Geographies* 2022, **2**:12-30.

This study presents long-term projections of the migratory grasshopper (Melanoplus sanguinipes) populations in several states in the USA under different climate change scenarios. They model nymph and adult densities as a Poisson point processes with an intensity parameter given by a random Gaussian field while jointly modelling location patterns in the survey to account for the preferential sampling of opportunistic data in areas occupied by the grasshopper. They found that alteration of precipitations and temperatures as predicted by climate models will cause the increase of population sizes and strong spatial variations in recruitment rates by 2040.

32. Meynard CN, Gay PE, Lecoq M, Foucart A, Piou C, Chapuis MP: **Climate-driven geographic distribution of the desert locust during recession periods: subspecies' niche differentiation and relative risks under scenarios of climate change**. *Glob Change Biol* 2017, **23**:4739-4749.

33. Aragon P, Coca-Abia MM, Llorente V, Lobo JM: **Estimation of climatic favourable areas for locust outbreaks in Spain: integrating species' presence records and spatial information on outbreaks**. *J Appl Entomol* 2013, **137**:610-623.

34. Kistner-Thomas E, Kumar S, Jech L, Woller DA: **Modeling rangeland grasshopper (Orthoptera: Acrididae) population density using a landscape-level predictive mapping approach**. *J Econ Entomol* 2021, **114**:1557-1567.

35. Zhang N, Zhang HY, He B, Gexigeduren, Xin ZY, Lin H: **Spatiotemporal heterogeneity of the potential occurrence of *Oedaleus decorus asiaticus* in Inner Mongolia steppe habitats.** *J Arid Environ* 2015, **116**:33-43.

36. Zheng SD, Zheng JH, Mu C, Ni YF, Dawuti B, Wu JG, IEEE: **Gis-based multi-criteria analysis model for identifying probable sites of locust outbreak in Xinjiang, China**, in *Proceedings of the 23rd International Conference on Geoinformatics (Geoinformatics) Jun 19–21*; China Univ Geosciences, Wuhan, Peoples R China: IEEE. 2015.

37. Cheke RA, Young S, Wang X, Tratalos JA, Tang SY, Cressman K: **Evidence for a causal relationship between the solar cycle and locust abundance**. *Agronomy* 2021, **11**:69.

38. Deveson T, Hunter D: **The operation of a GIS-Based decision support system for Australian locust management**. *Insect Sci* 2002, **9**:1-12.

39. Hunter D, Deveson T: **Forecasting and management of migratory pests in Australia**. *Insect Sci* 2002, **9**:13-25.

40. Dong YY, Xu F, Liu LY, Du XP, Ren BY, Guo AT, Geng Y, Ruan C, Ye HC, Huang WJ, *et al*.: **Automatic system for crop pest and disease dynamic monitoring and early forecasting**. *IEEE J Sel Top Appl Earth Obs Remote Sens* 2020, **13**:4410-4418.

41. Fisker EN, Bak J, Niassy A: **A simulation model to evaluate control strategies for the grasshopper *Oedaleus senegalensis* in West Africa**. *Crop Prot* 2007, **26**:592-601.

42. Axelsen JA, Petersen BS, Maiga IH, Niassy A, Badji K, Ouambama
• Z, Sønderskov M, Kooyman C: **Simulation studies of Senegalese grasshopper ecosystem interactions II: the role of egg pod predators and birds**. *Int J Pest Manag* 2009, **55**:99-112.

The authors developed an ecosystem dynamic model to compare the performance of a biocontrol agent vs chemical pesticide for the control of *O. senegalensis* population. They showed a clear negative effect of temperature on the efficiency of Green Muscle® and no substantial effect of bird predators on nymphs and adults. Their results revealed an important role of egg-pod-predator, which cannot be replaced by chemical pesticides. The model has been an operational tool for the implementation of treatments in Niger, Burkina Faso, Mali and Senegal.

43. Maiga IH, Axelsen JA, Badji K, Kooyman C: **Simulation studies of Senegalese grasshopper ecosystem interactions III: optimization of grasshopper control**. *Int J Pest Manag* 2009, **55**:113-120.

44. Bal AB, Ouambama Z, Moumouni A, Dieng I, Maiga IH, Gagare S, Axelsen JA: **A simple tentative model of the losses caused by the Senegalese grasshopper, *Oedaleus senegalensis* (Krauss 1877) to millet in the Sahel**. *Int J Pest Manag* 2015, **61**:198-203.

45. Cressman K: **Desert Locust Guidelines: Information and Forecasting**. FAO; 2001.

46. Pedgley D: **Desert Locust Forecasting Manual. Volumes I and II**. Centre for Overseas Pest Research; 1981.

47. FAO: **General Situation during June 2022, Forecast until mid-August 2022**. Desert Locust Bulletin vol. 525, FAO-Desert Locust Information Service; 2022.

48. Cressman K: **Technical Innovations in Global Early Warning in Support of Desert Locust Area-wide Management**. Hendrichs J, Pereira R, Vreysen MJB. Crc Press-Taylor & Francis Group; 2021.

49. Healey RG, Robertson SG, Magor JT, Pender J, Cressman K, GIS A: **for desert locust forecasting and monitoring**. *Int J Geogr Inf Syst* 1996, **10**:117-136.

50. Symmons PM, Green SM, Robertson RA, Wardhaugh KG: **The production of distribution maps of the incubation and hopper development periods of the Desert locust *Schistocerca gregaria* (Forsk.) (Orthoptera, Acrididae)**. *Bull Entomol Res* 1974, **64**:443-451.

51. Reus JAWA, Symmons PM: **A model to predict the incubation and Nymphal development periods of the Desert locust, *Schistocerca gregaria* (Orthoptera: Acrididae)**. *Bull Èntomol Res* 1992, **82**:517-520.

52. NOAA: **HYSPLIT Locusts: Locust Forecast Web App**. HYSPLIT Model. Air Resources Laboratory of the National Oceanic and Atmospheric Administration. US: NOAA; 2022.

53. Tabar M., Gluck J., Goyal A., Jiang F., Morr D., Kehs A., Lee D., Hughes D.P., Yadav A.: **A PLAN for tackling the locust crisis in East Africa: harnessing spatiotemporal deep models for locust movement forecasting**, in *Proceedings of the 27th ACM SIGKDD Conference on Knowledge Discovery & Data Mining*. 2021:3595–3604.

54. Tumelero F, da Silveira VC, Weymar GJ, Buske D, de Quadros RS, Gonçalves GA, de Athayde AS, Piovesan LR, da Cunha, Furtado I: **Simulation of the movement of a locust swarm in Argentina in 2020**. *Neotrop Entomol* 2021, **50**:716-724.

55. Klein I, Oppelt N, Kuenzer C: **Application of remote sensing data for locust research and management-a review**. *Insects* 2021, **12**:36.

56. Rhodes K, Sagan V: **Integrating remote sensing and machine learning for regional-scale habitat mapping: advances and future challenges for desert locust monitoring**. *IEEE Geosci Remote Sens Mag* 2022, **10**:289-319.

57. Hernández Zul JA, Quijano Carranza JA, Yáñez López R, Ocampo Velázquez RV, Torres Pacheco I, Guevara González RG, Castro, Ramírez AE: **Dynamic simulation model of Central American locust *Schistocerca piceifrons* (Orthoptera: Acricidae)**. *Fla Èntomol* 2013, **96**:1274-1283.

58. Despland E: **Fractal index captures the role of vegetation clumping in locust swarming**. *Funct Ecol* 2003, **17**:315-322.

59. Despland E, Rosenberg J, Simpson SJ: **Landscape structure and locust swarming: a satellite's eye view**. *Ecography* 2004, **27**:381-391.

60. Liu DZ, Zhao SY, Yang XM, Wang R, Cang XZ, Zhang HW, Hu C, Wyckhuys KAG, Wu KM: **Radar monitoring unveils migration dynamics of the yellow-spined bamboo locust (Orthoptera: Arcypteridae)**. *Comput Electron Agric* 2021, **187**:106306.

61. Gay P-E, Trumper E, Lecoq M, Piou C: **Importance of human capital, field knowledge and experience to improve pest locust management**. *Pest Manag Sci* 2021, **77**:5463-5474.

62. Rainey RC: **Migration and Meteorology: Flight Behaviour and the Atmospheric Environment of Locusts and Other Migrant Pests**. Clarendon Press; 1989.

63. Betts E.: **Forecasting infestations of tropical migrants pests: the Desert locust and the African Armyworm**, in *Insect flight. 7th Symposium of the Royal Entomological Society of London.* Edited by Rainey RC. 1976:113–134.

64. Hostetler JA, Chandler RB: **Improved state-space models for inference about spatial and temporal variation in abundance from count data**. *Ecology* 2015, **96**:1713-1723.

65. Vacik H, Lexer MJ: **Application of a spatial decision support system in managing the protection forests of Vienna for sustained yield of water resources**. *Ecol Manag* 2001, **143**:65-76.

66. Van der Werf W, Woldewahid G, Van Huis A, Butrous M, Sykora K: **Plant communities can predict the distribution of solitarious desert locust *Schistocerca gregaria***. *J Appl Ecol* 2005, **42**:989-997.

67. van der Valk H, Everts JW: Directives sur le Criquet Pèlerin 6: Précautions d′usage Pour la Santé Humaine et L′environnement vol. 6, FAO; 2003.