Remote Sensing Applications to Support Locust Management and Research

Evaluating the Potential of Earth Observation for Locust Outbreaks in Different Regions

Kumulative Dissertation zur Erlangung des Doktorgrades der Mathematisch-Naturwissenschaftlichen Fakultät der Christian-Albrechts-Universität zu Kiel

vorgelegt von

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Title picture: Italian locust (*Calliptamus italicus*) female adults during oviposition in Kazakhstan

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English Summary

Plagues and outbreaks of locusts have caused famine, harvest failure and negative impacts on grazing livestock ever since mankind became sedentary. Reports of catastrophic locust plagues are documented in numerous historical and religious writings and affected all continents except Antarctica.

With the accompanying industrialization and progress in agriculture, as well as the transformation of natural areas, locust infestations and outbreaks have declined since the second half of the 20th century. On the one hand, natural habitats of various locust species were transformed and used by humans, so that locust population dynamics were automatically contained by anthropogenic activities alone. On the other hand, the progress and use of insecticides as a control measure against locusts led to shorter and less intensive outbreak events. However, the large-scale and extensive use of chemicals negatively impact the environment and human health.

In order to minimize the use of insecticides and maximize their effectiveness, the so-called preventive locust management has been introduced since the 1960s. The goal of preventive locust management is to have a continuous, standardized and timely close-meshed observation of all relevant environmental parameters, as well as locust life cycles and phases. In this way, it aims at enabling locust population control as early as possible and contain potential outbreaks in their initial phase and at a small geographic scale. Considering the necessity of large-scale monitoring of habitats as well as environmental and weather conditions, the usage of satellite-based data and remote sensing methods have proven to be extremely beneficial since the 1980s. In detail, remote sensing data allows for the assessment of the situation on large and highly remote or difficult-to-access areas.

In the last ten years, there has been a tremendous boost in the development of satellite data and computer technology. Nowadays, many remote sensing datasets with high spatial and temporal resolution and historical archives are freely available to the public. Furthermore, data processing with the possibilities of modern computer technology and cloud-based applications offer new perspectives that were unimaginable just a few years ago. This constellation of data availability and the advanced technical possibilities of data processing bring new perspectives also for locust management and research.

In this context, this dissertation focuses on satellite remote sensing applications for locust management and additional contributions to locust research. Specifically, the remote sensing-based characterization and interpretation of land surface cover and its dynamics are addressed with a special emphasis on the requirements of different locust species. At first, the aim of this dissertation is to provide a holistic overview of the existing applications using satellite data focusing on different locust species and thus, to present current and new opportunities. Furthermore, remote sensing and geospatial datasets are used in a model to categorize areas with ideal and less than ideal conditions for locust outbreaks. The benefit of up-to-date remote sensing data for preventive locust management is demonstrated using time-series-based Sentinel-2 land cover classification. Due to the diversity of the numerous locust species and their spatial distribution in different geographical locations, this research focuses mainly on two locust species, the Italian locust *(Calliptamus italicus*) and the Moroccan locust (*Dociostaurus maroccanus*), as well as on selected study areas within their extensive habitats, respectively. Both selected locust species caused numerous damages in Europe, the Caucasus, Central Asia and North Africa in the past. For both species, there is only a limited number of publications exploiting the capabilities of remote sensing methods. Therefore, this dissertation aims to explore the potential approaches of Earth observation datasets to support preventive locust management and research for both species.

In the view of described challenges and opportunities, four major objectives are delineated in the present dissertation. As first part of this dissertation, a systematic review on available applications of remote sensing data in the context of locust management and research is provided. The focus of the review is on the various sensor types, indices and methods applied, as well as on thematic topics, that are categorized by species and geographic study areas. The results of this review form the basis for further methodological developments within this dissertation. In more detail, the results show that within the international literature, previous studies on remote sensing applications in the context of locust management and research mainly investigated the desert locust (*Schistocerca gregaria* 33%), migratory locust (*Locusta migratoria* 27%) and Australian plague locust (*Chortoicetes terminifera* 14%). Only few studies exist that deal with the Italian locust (5%) and the Moroccan locust (1%).

In the second part of this dissertation, a so-called Habitat Suitability Index (HSI) model was applied in order to better describe the habitats of the Italian locust and the Moroccan locust and to identify possible hotspot regions of their breeding sites. The HSI model considers favorable static and dynamic environmental variables derived from remote sensing datasets and factors that counteract successful breeding of locusts. Here, it is crucial to define species-specific characteristics and to take them into account within the model. The modelling results show that satellite datasets with high temporal and spatial resolution have significant potential to better categorize locust habitats in terms of suitability for successful breeding and population development.

Third, the current outbreak of the Moroccan locust in Sardinia, Italy, in the year 2022 was analyzed based on Sentinel-2 time-series and land cover classification approaches. This analysis quantifies, in an unprecedented way, the relationship between land cover types and land management information derived from remote sensing data and breeding locations during the outbreak. The integration of field survey data showed that a total of 43% of the detected locations were found to be in areas which were previously cultivated (e.g., fallow fields, untilled, pastureland). The relationship between the previous and current land management activities, as well as vegetation development within the locust breeding areas demonstrate that remote sensing data as well as up-to-date and task specified land cover applications can be an additional advantage for preventive locust management and research.

Finally, the benefits of using remote sensing and geospatial datasets for locust management are discussed and exemplified. Because practical applications of remote sensing and geospatial datasets are still not exploited fully in practice, this dissertation presents a system that standardizes the spatial information with the aim to facilitate a broader usage of such

datasets. The presented system provides a straightforward approach for professionals without geo-data-based training to apply spatial datasets in a simplified format for everyday analyses, assessments and planning.

Overall, this dissertation demonstrates that remote sensing applications for preventive locust management and research, especially for the Italian locust (*Calliptamus italicus*) and the Moroccan locust (*Dociostaurus maroccanus*), still have a lot of potential. This potential has not yet been sufficiently utilized especially considering the recent scientific developments. Even though remote sensing data plays a crucial role e.g., for the management of the desert locust and the Australian plague locust, there are barely any remote sensing-based applications for many other dangerous locust species. On the one hand, this is due to the different characteristics of the habitats and environmental factors that can favor the outbreaks of different species. On the other hand, there is comparatively low international research interest in many species, because they only have a regional or at most continental damage potential. With ongoing climate change and continuing alterations in land management activities, e.g., due to political, economic or security reasons, it remains an important task to derive remotely sensed information for all locust pests in order to support preventive management activities. In particular, it is of great importance to keep potential outbreaks to a minimum and at the same time the use of insecticides as effective and as low as possible. In this context, it should be mentioned that locusts are extremely resourceful for human and animal nutrition due to their high protein content. However, it is important that the insects for consumption are not contaminated by chemicals. Within the balancing act of locust control and harvest as well as exacerbating impacts of climate change and land management alteration, remote sensing data and methods will play an even more important role in future.

Zusammenfassung

Heuschreckenplagen und -ausbrüche führen seit Sesshaftwerdung des Menschen immer wieder zu Hungersnöten, Ernteausfällen und Beeinträchtigungen der Weidetierhaltung. Berichte über katastrophale Heuschreckenplagen finden sich in zahlreichen historischen und religiösen Schriften und betrafen bereits alle Kontinente mit Ausnahme der Antarktis.

Mit einhergehender Industrialisierung, Fortschritten in der Landwirtschaft, sowie der Umgestaltung von Naturräumen durch den Menschen, sind seit der zweiten Hälfte des 20. Jahrhunderts Heuschreckenplagen und -ausbrüche zurückgegangen. Zum einen wurden die natürlichen Habitate verschiedener Heuschreckenarten umgestaltet und vom Menschen genutzt, sodass die Heuschreckenpopulationsdynamik schon allein durch die menschliche Aktivität eingedämmt wurde. Zum anderen führte der Fortschritt und Einsatz von Insektiziden als Bekämpfungsmaßname gegen Heuschrecken zu kürzeren und weniger intensiven Ausbruchsereignissen. Dabei ist ein großräumiger und massiver Einsatz von Chemikalien mit all seinen negativen Auswirkungen auf die Umwelt und den Menschen die Kehrseite.

Um den Einsatz mit Insektiziden möglichst gering aber maximal effektiv zu gestalten, wird beim sogenannten Heuschreckenmanagement seit den 1960er Jahren auf präventive Strategien gesetzt. Die wesentliche Aufgabe innerhalb des präventiven Heuschreckenmanagements ist eine kontinuierliche und engmaschige Beobachtung aller relevanten Umweltparameter, sowie der Heuschreckenlebenszyklen und -phasen. Somit soll eine möglichst kleinräumige und frühzeitige Bekämpfung ermöglicht werden, um potentielle Ausbrüche bereits in ihrer Anfangsphase einzudämmen. Vor allem bei der großräumigen Beobachtung der Habitate sowie der Umweltsituation und Wetterlage hat sich der Einsatz von Fernerkundungsdaten und -methoden seit den 1980er Jahren als äußerst vorteilhaft herausgestellt. Des Weiteren ermöglichen Fernerkundungsdaten eine Abschätzung der Situation auch in stark abgelegenen oder schwer zugänglichen Gebieten.

In den letzten zehn Jahren gab es einen enormen Entwicklungsschub hinsichtlich der Verfügbarkeit von Satellitendaten sowie im Bereich der Computertechnologie. So sind heutzutage viele Daten mit hoher räumlicher und zeitlicher Auflösung sowie historische Archive öffentlich zugänglich. Des Weiteren bieten moderne Computertechnologien und cloudbasierte Prozessierungsumgebungen neue Anwendungsperspektiven, die noch vor einigen Jahren unvorstellbar waren. Diese Konstellation aus Datenverfügbarkeit und den fortgeschrittenen technischen Möglichkeiten der Datenverarbeitung bringen neue Potentiale auch für das präventive Heuschreckenmanagement und entsprechende Forschungsansätze.

Vor diesem Hintergrund beschäftigt sich die vorliegende Dissertation mit dem Einsatz der Satellitenfernerkundung im Bereich Heuschreckenmanagement und -forschung. Die fernerkundungsbasierte Charakterisierung und Interpretation der Landoberflächenbedeckung und deren Dynamik stehen dabei - mit Fokus auf die Anforderungen der verschiedenen Heuschreckenarten - im Vordergrund. Ziel dieser Dissertation ist es

zunächst, einen ganzheitlichen Überblick über vorhandene Anwendungen von Satellitendaten im Kontext Heuschreckenmanagement zu erarbeiten. Des Weiteren werden fernerkundungs- und geobasierten Datensätzen in einem Model verwendet, um Flächen mit idealen bzw. weniger idealen Bedingungen für Heuschreckenausbrüche zu kategorisieren. Der Vorteil von aktuellen Fernerkundungsdaten für präventives Heuschreckenmanagement wird anhand zeitreihenbasierten Sentinel-2 Landbedeckungsklassifikation demonstriert. Aufgrund der Vielfältigkeit der zahlreichen Heuschreckenarten und deren räumlicher Verteilung in verschiedenen geographischen Lagen, konzentriert sich diese Arbeit im Wesentlichen auf zwei Heuschreckenarten, die Italienische Schönschrecke (*Calliptamus italicus*) und die Marokkanische Wanderheuschrecke (*Dociostaurus maroccanus*), sowie auf ausgewählte Studiengebiete innerhalb deren weiträumigen Habitaten. Beide Heuschreckenarten verursachten zahlreiche Ausbrüche in der Vergangenheit mit Schäden in Europa, dem Kaukasus, Zentralasien und Nordafrika. Für beide Heuschreckenarten existieren nur wenige Forschungsarbeiten, die sich mit der Anwendung von Fernerkundungsdaten auseinandersetzen. Vor diesem Hintergrund zielt diese Dissertation auf die Entwicklung von relevanten Methoden unter Einsatz von Fernerkundungsdaten für beide Heuschreckenarten ab, um präventives Heuschreckenmanagement und -forschung zu unterstützen.

Angesichts der beschriebenen Herausforderungen und Möglichkeiten werden in der vorliegenden Dissertation vier Hauptziele skizziert. Zunächst wird ein umfassender Überblick zu bereits vorhandenen Anwendungen von Fernerkundungsdaten im Zusammenhang mit Heuschreckenmanagement und -forschung erarbeitet. Hierbei stehen sowohl die verwendeten Fernerkundungssensoren, Indizes und Methoden als auch die inhaltlichen Schwerpunkte relevanter Studien im Vordergrund. Diese werden zudem nach untersuchten Heuschreckenarten und Studiengebieten kategorisiert. Die Ergebnisse der Literaturstudie bilden dann die Grundlage für weitere methodische Entwicklungen innerhalb dieser Arbeit. Die herausgearbeiteten Ergebnisse der Literaturrecherche zeigen, dass die in der internationalen Literatur vorhandenen Studien zum Thema, Einsatz der Fernerkundung im Bereich Heuschreckenmanagement bzw. Heuschreckenforschung, sich hauptsächlich mit der Wüstenheuschrecke (*Schistocerca gregaria* 33%), der Wanderheuschrecke (*Locusta migratoria* 27%) und der Australischen Pestheuschrecke (*Chortoicetes terminifera* 14%) beschäftigen. Ebenso zeigt die Literaturrecherche, dass nur wenige Untersuchungen zur Italienischen Schönschrecke (5%) und der Marokkanischen Wanderheuschrecke (1%) existieren.

Im zweiten Teil dieser Arbeit wurde ein sogenanntes „Habitat Suitability Index Model“ angewendet um die Habitate der Italienischen Schönschrecke und der Marokkanischen Wanderheuschrecke besser zu beschreiben und eventuelle Hotspotregionen für Brutstätten zu identifizieren. Das Modell berücksichtigt sowohl begünstigende statische und dynamische Umweltfaktoren, als auch Faktoren, welche einem erfolgreichen Schlüpfen und der Vermehrung von Heuschrecken entgegenwirken. Dabei war es von enormer Bedeutung artenspezifische Charakteristika herauszuarbeiten und im Modell entsprechend zu berücksichtigen. Die Ergebnisse der Modellierung zeigen, dass der Einsatz von zeitlich und räumlich hochaufgelösten Satellitendaten hohes Potential hat, um die Habitate von

Heuschrecken bzgl. ihrer Eignung für ein erfolgreiches Schlüpfen und eine erfolgreiche Populationsentwicklung besser zu kategorisieren.

Drittens, wurde der Ausbruch der Marokkanischen Wanderheuschrecke auf Sardinien (Italien) aus dem Jahr 2022 auf der Grundlage von Sentinel-2 Zeitreihen und Methoden der Landbedeckungsklassifizierung analysiert. Diese Analyse quantifiziert auf beispiellose Weise den Zusammenhang von Landbedeckungstypen und Landmanagement, welche aus Fernerkundungsdaten abgeleitet wurden, mit beobachteten Brutgebieten während des Ausbruchs. Die Analysen haben gezeigt, dass sich insgesamt 43% der in der Feldbegehung erfassten Standorte der Brutgebiete auf Flächen befinden, die zuvor kultiviert waren (z.B. Brachflächen, Ackerland, Weideland). Der daraus abgeleitete Zusammenhang zwischen früherer sowie aktueller Landbewirtschaftung und der Vegetationsentwicklung in Heuschreckenbrutgebieten verdeutlicht, dass Fernerkundungsdaten und aktuelle sowie aufgabenspezifische Landbedeckungsklassifikationen von Vorteil für das präventive Heuschreckenmanagement und -forschung sein können.

Schlussendlich werden die Vorteile des Einsatzes von fernerkundungs- und geobasierten Datensätzen für das Heuschreckenmanagement diskutiert und der Nutzen dieser Daten beispielhaft aufgezeigt. Da der Einsatz von fernerkundungs- und geobasierten Datensätzen in der Praxis immer noch nicht das vorhandene Potenzial ausschöpft, wird in dieser Arbeit ein System präsentiert, welches die räumlichen Informationen standardisiert, mit dem Ziel, eine breitere Nutzung solcher Datensätze zu ermöglichen. Dies soll Fachkräften ohne geodatenbasierte Ausbildung eine Grundlage bietet, um bestehende Daten und Informationsprodukte in vereinfachter Form für alltägliche Analysen, Einschätzungen und Planungen zu nutzen.

Insgesamt veranschaulicht diese Arbeit, dass Fernerkundungsdaten und -methoden bzgl. des Heuschreckenmanagements und diesbezüglicher Forschung mit Fokus auf die Italienische Schönschrecke (*Calliptamus italicus*) und Marokkanische Wanderheuschrecke (*Dociostaurus maroccanus*) noch viel Potential haben. Die vor allem durch die technologischen Entwicklungen der letzten Jahre verbesserten Möglichkeiten des Einsatzes fernerkundungsbasierter Methoden werden noch nicht ausreichend ausgeschöpft. Auch wenn Fernerkundungsdaten eine entscheidende Rolle z.B. für das Management der Wüstenheuschrecke und der Australischen Pestheuschrecke spielen, gibt es für viele andere gefährliche Arten wenig oder kaum fernerkundungsbasierte Anwendungen und Methoden. Dies liegt zum einen an den unterschiedlichen Charakteristika der Habitate und Umweltfaktoren, die die Ausbrüche von verschiedenen Arten begünstigen können. Zum anderen am vergleichsweise geringen internationalen Forschungsinteresse, aufgrund der Vielzahl an Arten, die ein eher regionales bzw. kontinentales Schadenspotential aufweisen. Unter der Annahme eines weiter fortschreitenden Klimawandels und sich immer wieder ändernder menschlicher Landnutzung - sei es aus politischen, wirtschaftlichen oder sicherheitstechnischen Gründen - ist es auch in Zukunft wichtig für alle gefährlichen Heuschreckenarten fernerkundungsbasierte Informationen abzuleiten, um ein präventives Heuschreckenmanagement zu unterstützen. Besonders wichtig ist es, die potentiellen Ausbruchsherde minimal, aber auch den Einsatz von Insektiziden möglichst effektiv und gering zu halten. In diesem Zusammenhang sei auch erwähnt, dass Heuschrecken aufgrund des hohen Proteingehalts großes Potenzial zur Unterstützung der Ernährungssicherheit (für

Mensch oder Tier) haben. Dabei ist es wichtig, dass die Insekten für den Verzehr zuvor nicht durch Chemikalien kontaminiert werden. Bei diesem Spagat zwischen der Heuschreckenbekämpfung auf der einen Seite und der Heuschreckenverzehr auf der anderen Seite, könnten Daten und Methoden der Fernerkundung in Zukunft eine zunehmend wichtige Rolle spielen.

Russian Summary

Вспышки и нашествия саранчи вызывали голод, неурожай и негативное воздействие на пастбищный скот с тех пор, как человечество стало оседлым. Информация о катастрофических нашествиях саранчи задокументированы в многочисленных исторических и религиозных писаниях и затронули все континенты, кроме Антарктиды.

В ходе индустриализации и развития сельского хозяйства, а также преобразованием природных зон, со второй половины 20 века численность и вспышки саранчи сократились. С одной стороны, естественные места обитания различных видов саранчовых преобразовались и стали использоваться человеком, соответственно динамика численности саранчовых автоматически сдерживалась. С другой стороны, прогресс и использование инсектицидов в качестве меры борьбы с саранчой привели к более коротким и менее интенсивным вспышкам. Однако масштабное и широкое применение химических веществ негативно влияет на окружающую среду и здоровье человека.

Для того чтобы минимизировать использование инсектицидов и максимально повысить их эффективность, с 1960-х годов внедряются методы контроля и управления саранчовыми. Целью управления саранчовых является постоянное, стандартизированное и своевременное наблюдение за всеми соответствующими параметрами окружающей среды, а также за жизненными циклами и фазами саранчи. Таким образом, обеспечить контроль популяции саранчи как можно раньше и сдержать потенциальные вспышки на начальной стадии и в небольших географических масштабах. Учитывая необходимость крупномасштабного мониторинга мест обитания, а также состояния окружающей среды и погоды, использование спутниковых данных и методов дистанционного зондирования оказалось чрезвычайно полезным с 1980-х годов. В частности, данные дистанционного зондирования позволяют оценить ситуацию на больших и очень удаленных или труднодоступных территориях.

За последние десять лет произошел огромный скачок в развитии спутниковых данных и компьютерных технологий. В настоящее время многие наборы данных дистанционного зондирования с высоким пространственным и временным разрешением, и исторические архивы находятся в свободном доступе. Кроме того, обработка данных с использованием возможностей современных компьютерных технологий и облачных приложений открывает новые перспективы, которые невозможно было представить еще несколько лет назад. Это сочетание доступности данных и передовых технических возможностей обработки данных открывают новые перспективы для контроля саранчовых и исследований в том числе.

Данная диссертация раскрывает тему применения спутникового дистанционного зондирования для контроля саранчовых и проведения дополнительных исследований саранчи. В частности, особое внимание уделяется изучению потребностей различных видов саранчовых при описании характеристик земного покрова и его динамики на

основе данных дистанционного зондирования. Первостепенная цель данной диссертации состоит в том, чтобы предоставить целостный обзор существующих приложений, использующих спутниковые данные, в разрезе различных видов саранчовых для того, чтобы раскрыть текущие и потенциальные возможности. Кроме того, дистанционное зондирование и наборы геопространственных данных используются для классификации территорий с идеальными и не идеальными условиями для нашествий саранчи. Преимущества современных данных дистанционного зондирования для контроля саранчовых продемонстрированы с помощью классификации почвенно-растительного покрова на основе временных рядов Sentinel-2. Из-за разнообразия многочисленных видов саранчовых и их пространственного распределения в разных географических точках, исследование сосредоточено в основном на двух видах саранчи, итальянского пруса (*Calliptamus italicus*) и марокканской саранче (*Dociostaurus maroccanus*), а также на определенных территориях, в пределах их обширного местообитаний. Оба вида саранчи в прошлом нанесли многочисленные повреждения в Европе, на Кавказе, в Центральной Азии и Северной Африке. Ограниченное количество публикаций имеется об обоих видах, где используются возможности методов дистанционного зондирования. Таким образом, целью данной диссертации является изучение потенциальных методов применения наборов данных наблюдения Земли для поддержки профилактических мероприятий по борьбе с саранчой и исследований обоих видов.

С учетом описанных проблем и возможностей в настоящей диссертации обозначены четыре основные цели. В качестве первой части этой диссертации представлен систематический обзор доступных приложений данных дистанционного зондирования в контексте контроля саранчовых и научных исследований. Основное внимание в обзоре уделяется различным типам датчиков, индексам и применяемым методам, а также тематикам, классифицированным по видам и географическим областям исследования. Результаты этого обзора составляют основу для дальнейших методологических разработок в рамках данной диссертации. Результаты изучения показывают, что в международной литературе предыдущие исследования по применению дистанционного зондирования для контроля и изучения саранчовых, в основном изучалась пустынная саранча (*Schistocerca gregaria* 33%), перелетная саранча (*Locusta migratoria* 27%) и австралийская саранча (*Chortoicetes terminifera* 14%). Существует лишь несколько исследований, посвященных итальянского пруса (5%) и мароккской саранче (1%).

Во второй части диссертации была применена так называемая модель индекса пригодности местообитаний (HSI), для того чтобы лучше описать места обитания итальянского пруса и мароккской саранчи и определить возможные очаги их размножения. Модель HSI учитывает благоприятные статические и динамические переменные окружающей среды, полученные благодаря данным дистанционного зондирования, и факторы, препятствующие успешному размножению саранчи. Здесь важно определить видоспецифические характеристики и учесть их в модели. Результаты моделирования показывают, что наборы спутниковых данных с высоким временным и пространственным разрешением обладают значительным потенциалом для лучшей классификации местообитаний саранчовых с точки зрения их пригодности для успешного размножения и развития популяции.

В-третьих, вспышка мароккской саранчи на Сардинии, Италия, в 2022 году была проанализирована на основе временных рядов Sentinel-2 и методов классификации земного покрова. Этот анализ дает беспрецедентную количественную оценку взаимосвязи между типами земного покрова и информации об использовании земельных ресурсов, полученной на основе данных дистанционного зондирования и мест размножения во время вспышки. Интеграция данных полевого обследования показала, что в общей сложности 43% выявленных местонахождений находились на ранее возделываемых территориях (например, залежи, пашни, пастбища). Связь между предыдущей и текущей деятельностью по землеустройству, а также развитие растительности в районах размножения саранчи показывает, что данные дистанционного зондирования, а также актуальные и конкретизированные по задачам приложения изучения почвенного покрова, могут стать дополнительным преимуществом для контроля и борьбы с саранчовыми и исследований.

Наконец, обсуждаются и приводятся примеры преимуществ использования дистанционного зондирования и наборов геопространственных данных для борьбы с саранчой. Поскольку практическое применение наборов данных дистанционного зондирования и геопространственных данных все еще не используется в полной мере на практике, в данной диссертации представлена система, которая стандартизирует пространственную информацию с целью содействия более широкому использованию таких наборов данных. Представленная система обеспечивает простой подход для специалистов, не имеющих подготовки в области геоданных, к применению пространственных наборов данных в упрощенном формате для повседневного анализа, оценки и планирования.

В целом, данная диссертация показывает, что применение дистанционного зондирования для контроля и исследования саранчи, особенно итальянского пруса (*Calliptamus italicus*) и марокканской саранчи (*Dociostaurus maroccanus*), все еще имеет большой потенциал. Этот потенциал еще недостаточно использован, особенно с учетом последних научных разработок. Несмотря на то, что данные дистанционного зондирования играют решающую роль, например, для борьбы с пустынной саранчой и австралийской саранчой, для многих других опасных видов саранчи практически нет приложений, основанных на дистанционном зондировании. С одной стороны, это связано с различными характеристиками мест обитания и экологическими факторами, которые могут благоприятствовать вспышкам различных видов. С другой стороны, международный исследовательский интерес ко многим видам сравнительно невелик, поскольку они имеют лишь региональный или, в крайнем случае, континентальный потенциал ущерба. В условиях продолжающегося изменения климата и постоянных изменений в деятельности по управлению земельными ресурсами, например, по политическим, экономическим причинам или причинам безопасности, остается важной задачей получение информации дистанционного зондирования для всех саранчовых вредителей с целью их контроля и управления. В частности, очень важно свести потенциальные вспышки к минимуму и в то же время использовать инсектициды как можно эффективнее и реже. В этом контексте следует отметить, что саранча чрезвычайно питательна людей и животных, благодаря высокому содержанию белка. Однако важно, чтобы насекомые, используемые для потребления, не содержали химические вещества. В целях сбалансирования борьбы с саранчой и сбором урожая, а также усугубляющегося воздействия изменения климата и изменения землепользования, данные и методы дистанционного зондирования будут играть еще более важную роль в будущем.

Figures

Tables

Abbreviations and Acronyms

ALOS	Advanced Land Observing Satellite
APLC	Australian Plague Locust Commission
ARB	Awash River Basin
ARD	Analysis-Ready Data
ARTEMIS	Africa Real Time Environmental Monitoring Information System
ARVI	Atmospherically Resistant Vegetation Index
ASTER	Advanced Spaceborne Thermal Emission and Reflection Radiometer
AUC	Area Under the receiver operating characteristic Curve
AVHRR	Advanced Very High Resolution Radiometer
AWIFS	Advanced Wide Field Sensor
C°	Degree Celsius
CCI	Climate Change Initiative
CIT	Calliptamus italicus
CMORPH	Climate Prediction Center MORPHing
COPR	Centre for Overseas Pest Research
DEM	Digital Elevation Model
DFD	German Remote Sensing Data Center
DGG	Discrete Global Grid
DLIS	Desert Locust Information Service
DLR	German Aerospace Center
DMA	Dociostaurus maroccanus
ENM	Ecological Niche Modelling
ENVISAT	Environmental Satellite
EO	Earth Observing
ESA	European Space Agency
ETM+	Enhanced Thematic Mapper of Landsat-7
EVI	Enhanced Vegetation Index
FAO	United Nations Food and Agriculture Organization
FCover	Fraction of Vegetation Cover
FMASK	Function mask
GAM	Generalized Additive Models
GEE	Google Earth Engine
GIS	Geographic information systems
GLC	Global Land Cover
GLI	Global Locust Initiative
GLM	Generalized Linear Models
GPS	Global Positioning System

HSI	Habitat Suitability Index
Ha	Hectare
HSV	Hue, Saturation and Value
HTC	Hydrothermal Coefficient
IMR	Insect-Monitoring Radars
IRI	International Research Institute for Climate and Society
ISRIC	International Soil Reference and Information Centre
ITCZ	Intertropical Convergence Zone
Km	Kilometer
LAI	Leaf Area Index
LHI	Locust Hazard Index
LDI	Locust Density Index
LIDAR	Light Detection And Ranging (remote sensing technology)
LM	Long Microwave
LMI	Asian Migratory locust
IPCC	Intergovernmental Panel on Climate Change
LRI	Locust plague Risk Index
LST	Land Surface Temperature
LTA	Long Term Average
LULUC	Land Use and Land Cover Classification
MCA	Multi-Criteria Analysis
M	Meter
MERIS	Medium Resolution Imaging Spectrometer
Mm	Millimeter
MODIS	Moderate Resolution Imaging Spectroradiometer
MSAVI	Modified Soil Adjusted Vegetation Index
MSI	Mean shape index
MSS	Multi Spectral Scanner sensor
NA	Not Applicable
NASA	National Aeronautics and Space Administration
NCAR	National Center for Atmospheric Research
NCEP	National Center for Environmental Modelling
NDTI	Normalized Difference Tillage Index
NDVI	Normalized Difference Vegetation Index
NIR	Near Infrared
NPP	Net Primary Productivity
NRT	Near Real Time
NOAA	National Oceanic and Atmospheric Administration
OLI	Operational Land Imager
PB-AHP	Patch-based Analytic Hierarchy Process

PBAF	Potential Breeding Activity Factor
PCA	Principal component analysis
PVI	Perpendicular Vegetation Index
Radar	RAdio Detection and Ranging
RF	Random Forests
RGB	Red, Blue, Green
ROC	Receiver Operating Characteristic
SAR	Synthetic Aperture Radar
SAVI	Soil Adjusted Vegetation Index
SCI	Science Citation Index
SDM	Spatial Distribution Model
SET	Sum of Effective Temperature
SMAP	Soil Moisture Active Passive
SMOS	Soil Moisture and Ocean Salinity
SoH	Start of Hatching
SPOT	Satellite Pour l'Observation de la Terre
SRS	Satellite Remote Sensing
SRTM	Shuttle Radar Topography Mission
SVM	Support Vector Machine
SWIR	Short-Wave Infrared
SWOT	Surface Water and Ocean Topography
TCB	Tasseled Cap Brightness
TCG	Tasseled Cap Greenness
TCW	Tasseled Cap Wetness
TM	Thematic Mapper
TIR	Thermal Infrared
TSS	True Skill Statistic
UAV	Unmanned Aerial Vehicle
UN	United Nations
USGS	United States Geological Survey
VHR	Very-High-spatial-Resolution
VI	Vegetation Index
VIF	Variance Inflation Factor
W-MEAN	Weighted Mean
WMO	World Meteorological Organization

CHAPTER 1

1 Introduction

Biological disasters diminished global crop and livestock production between 2008 and 2018 by a total of nine percent (FAO, 2021). For the future, it is estimated that the global crop yield reduction caused by biological pests such as locusts, armyworm divers plant pathogens and weeds will be between 30 to 40% (Savary et al., 2019). One of the most dangerous invasive pests are locusts. Plagues and outbreaks of different locust species are ancient agricultural pests and can be dated several thousand years back almost everywhere around the world (Latchininsky, 1998; Le Gall et al., 2019; Zhang et al., 2019). Locust population can increase rapidly due to changing abiotic conditions and cause devastation to crops and pasture in a very short time. Swarms of locusts can migrate up to several hundred kilometers per day invading vast areas independent of country borders. According to Latchininsky (2013) pest species such as locusts and grasshoppers affect the livelihood of 10% of the world population. Additionally, locust plagues and outbreaks also harm natural vegetation which can lead to increased soil erosion and limited food sources for other animals and insects within affected ecosystems.

Despite technological progress and comparably less frequent and intense outbreaks over the past decades, locust outbreaks still affect food security and livelihoods, especially of rural population (Zhang et al., 2019). The scale of an outbreak depends on species, environmental conditions and anthropogenic influence. Outbreaks can occur either regularly, such as e.g. in African Sahel and China, or episodically with changing periods of invasion and recession, common for desert locust (*Schistocerca gregaria*) or Australian plague locust (*Chortoicetes terminifera*) (Zhang et al., 2019). Locust outbreaks usually evolve due to exceptional weather conditions or due to a combination of several environmental and anthropogenic factors. Heavy rains, prolonged droughts and land management play a crucial role. Recently, several outbreaks on continental, regional and local scale underlined, once again, that locusts maintain a serious threat leading to economic losses and affecting food security and social stability (Lecoq and Cease, 2022). This becomes even more important with growing world population, food insecurity for billions of people due to climate change and collapsing supply caused by armed conflicts and wars. Despite their destructive character for agriculture and pasture, locusts can be an additional source of food for human and livestock due to their high content of protein (van Huis, 2021). In this context, preventive management and, control of different locust species all over the world, as well as further research are essential.

1.1 The role of remote sensing for locust management and research

Locusts are grasshoppers of the family Acrididae (Orthoptera: *Acrididae*) including about 500 species capable of causing harm to agriculture, whereby around 50 species are actually considered as major agricultural pests (Zhang et al., 2019). The control of these highly destructive species is essential for food security, social and economic stability. Locust plagues (compare Table 1-1 for terminology) are sporadic and have the capacity to rapidly expand across large areas. Therefore, their control is critical for food security worldwide and often requires governmental or international involvement (Zhang et al., 2019). The improvement of locust control over the past 50+ years was initiated by a paradigm change from crop protection to preventive management (Hunter, 2004; Magor et al., 2008; Zhang et al., 2019). Preventive management is proactive and aims to detect the hazard of a locust population upsurge and control it on a smaller scale before it evolves into outbreaks or even into large scale plagues (Latchininsky, 2013). Preventive management includes a better understanding of the species biology and ecology, more effective monitoring, early warning system and different control strategies. Especially the monitoring of vast areas which provide favorable conditions for successful breeding and potential for locust population increase, are of high importance within preventive locust management strategies. This kind of geospatial risk assessment benefits highly from availability and quality of geospatial and remote sensing datasets. Therefore, the role of remote sensing data for locust management has been growing over the past decades (Cressman, 2013; Latchininsky, 2013).

Table 1-1. Locust related terminology for this thesis (adapted based on Zhang et al. (2019))

Terminology	Definition
Phase change	transition process between solitarious and gregarious phases of locusts in response to changes in population density
Upsurge	period following a recession marked by a very large increase in locust numbers
Outbreak	limited area where significant damage was caused
Plague	period of one or more years of widespread and heavy infestations of locust bands or swarms
Recession	period without widespread and heavy infestations by swarms
Preventive locust management	strategy aiming to control hotspots before damage occurs. Activities including monitoring (population dynamics, locust morphology, environment, weather), early warning, control, reporting
Locust control	measurements to counteract locust population increase (e.g. treatment with chemical, biological insecticides, soil tilling, introducing of natural enemies)

Satellite remote sensing-based research and various case study applications were important drivers to improve our understanding of locust-relevant ecological and environmental conditions and were first introduced by Pedgley (1974) and Hielkema (1977) for desert locust and later by Bryceson and Wright (1986) for Australian plague locust. Since then, available datasets from satellites have become important to assess favorable ecological conditions for locust breeding and population increase. Remote sensing-based forecast of regions with exceptional rainfall and monitoring the development of green vegetation are the main goals of desert and Australian plague locust early warning strategies (Bryceson et al., 1993; Cressman, 2013; Latchininsky, 2013). The main advantage of remote sensing data is the coverage of large areas at regular frequency (temporal resolution) because millions of hectares (ha) have to be monitored independent from country borders, accessibility or security. Therefore, remote sensing has played a significant part for preventive locust management by contributing to decision making with forecast of heavy rains, mapping vegetation development, and assessing favorable ecological conditions within locust habitats. In this way, it helps field teams to find hotspot regions and significantly reduce operative costs, increase reaction time and improve effectiveness of preventive locust management (Latchininsky, 2013). Remote sensing data application and comprehensive methods are well developed especially for desert locust and Australian plague locust. The Food and Agriculture Organization (FAO) of the United Nations (UN) operates successfully the Desert Locust Information Service (DLIS) (FAO, 2009, 2022). The Australian Plague Locust Commission (APLC) also implements satellite based weather forecast and different remote sensing datasets (Hunter, 2004). Similar efforts are under development for Central Asia and Caucasus region (FAO, 2021b).

1.2 The requirement for specific locust species consideration and regional perspectives

First of all, the standard convention on naming species is the common name, scientific name and abbreviated scientific name (Cullen et al., 2017). Many existing locust species, their naming convention and geographic distribution are summarized in Cullen et al. (2017), Le Gall et al. (2019), and Steedman (1990). Table 1-2 presents the three main species relevant for this thesis.

Efficient monitoring and control of any locust pest is based on the detailed knowledge of its biology and ecology (Latchininsky, 2013). Local and regional phytosanitary teams usually have comprehensive information on environmental and climatic factors (temperature, moisture, vegetation, soil and land-use) and how these variables affect different locust species of interest, and their interaction within the ecosystem and human activities (Scholthof, 2007). Since each species has its unique ecological niche, it is important to consider their specification in the context of remote sensing and geospatial data. Even though some methods can be transferred to different species, it is necessary to review and adapt all important variables under consideration from state-of-the-art literature and expert knowledge.

Table 1-2. Locust species relevant for this thesis.

Scientific Locust Name	Common Name	Scientific Abbreviation	Geographic Distribution
Calliptamus italicus (Linnaeus, 1758)	Italian locust	CIT	Europe, Central Asia, Mongolia and western Siberia
Dociostaurus maroccanus (Thunberg, 1815)	Moroccan locust	DMA	North Africa, Europe, Caucasus, Central Asia
Schistocerca gregaria gregaria (Forskål, 1775)	Desert locust	n.a.	North Africa, Middle East, Indian subcontinent, southern Europe

1.3 Research focus and objectives

Over the past years and decades, there have been many locust plagues and outbreaks of different scale and intensity all around the world. Changes in land management, political or security instability, as well as climate change affect locust population and can contribute to more outbreaks in future. In addition to all other factors which endanger food security (e.g. prolonged droughts, natural hazards, armed conflicts, various agricultural pests and diseases), the risk of destructive locust species cannot be neglected. The use of remote sensing data as an independent data source that is able to cover vast areas at different temporal resolutions, has been an important contribution to the progress of desert locust and Australian plague locust management over the past decades. Nevertheless, a lot of potential is still to be explored, especially for other dangerous locust species and regions. Within this context, four main research objectives are defined:

Objective 1: “Conduct a comprehensive review on international studies which have applied remote sensing data in the context of locust distribution, monitoring and forecast”

Integrated remote sensing applications for locust management and research studies have been published since the availability of Landsat and Advanced Very-High-Resolution Radiometer (AVHRR) data. This results in more than five decades of development for different locust species, regions and applications. Despite a few review studies on general applicability of remote sensing within locust research, a comprehensive categorized review does not exist. Therefore, this thesis provides a comprehensive overview, by grouping existing research based on different locust species and applications. To comply the first overarching objective, the following research questions are formulated and addressed:

Research Questions 1:

- Which locust species have been investigated by means of remote sensing applications?
- Where were remote sensing-based analyses for locust management and research conducted?
- Which satellite sensor types were used for locust management and research studies?
- What kind of remote sensing-based variables and indices were applied for locust management and research studies?
- What time periods are covered by remote sensing-based locust management and research studies?
- What are the thematical foci of the existing studies?

Objective 2: "Use different remote sensing and geospatial datasets to demonstrate the advantage of data combination and higher-resolution datasets such as Sentinel-2"

This objective focuses on the Habitat Suitability Index (HSI) model which takes advantage of different environmental variables, including Ecological Niche Modelling (ENM) results, time-series analyses of satellite data and species-specific knowledge to better discriminate areas providing optimal locust breeding and egg pod incubation conditions. Current climate, vegetation, land cover and land use conditions are considered for the three species of interest, the Italian locust in North Kazakhstan (Pavlodar oblast), the Moroccan locust in South Kazakhstan (Turkistan oblast) and the desert locust in the Awash River Basin (ARB) in Ethiopia, Djibouti and, Somalia. In this way, a high-resolution map of potential habitats for laying and surviving locust eggs is derived. The results are validated with ground truth data collected by field scouts. The derived information is relevant for the identification of habitat suitability of different locust species based on individual species preference and up-to-date data of the current land and climate situation. In this context, the following research questions are formulated and addressed:

Research Questions 2:

- How can unique locust species characteristics be included in modelling approaches?
- What kind of up-to-date climate and geospatial datasets can be used to conduct Ecological Niche Modelling (ENM) and Habitat Suitability Index (HSI) modelling for selected locust species?
- How can suitable conditions for locust breeding and potential population upsurge be better differentiated?
- What are the advantages of improving spatial resolution of modelled results?

Objective 3: “Analyze the recent Moroccan locust outbreak in Sardinia (Italy) from the perspective of remote sensing based on up-to-date land cover characteristics with focus on favorable conditions for this species”

The outbreak of Moroccan locust in Sardinia between 2019 and 2022 resulted from an ongoing drought period in this region in combination with changing land management. This objective aims to quantify the relationship between locust breeding sites during locust population increase, and previous and ongoing land management, as well as vegetation development. Time-series of Sentinel-2 data are exploited with the aim to map active cultivation and abandoned, fallow or untilled land. To address this objective, the following research questions shall be answered:

Research Questions 3:

- What are the relations between recent Moroccan locust outbreak in Sardinia and land cover characteristics derived from Sentinel-2 data?
- What kind of land surface was preferred by Moroccan locust for breeding during the outbreak?
- How can remote sensing analyses contribute to an early warning system and decision support to minimize higher risk concerning this agricultural pest?

Objective 4: “Demonstrate an application case for locust management, based on expert rule set exploiting remote sensing and geoscientific datasets”

Since many locust experts, field guards and locust managers have different levels of knowledge (sometimes not including application of geospatial and remote sensing data) the practical applicability must improve and, consequently may close the discrepancy between available spatial information sources and practice. This objective aims at combining important and available geospatial information with expert based practices. The goal is to simplify different pre-processing steps and provide a more practical base for locust managers. All necessary datasets are processed within a h3-hexagon system which allows straightforward application and rule development for locust managers without dealing with complex characteristics of different spatial datasets (e.g., data format, spatial and temporal resolution, projection). Such an assessment may support rapid decision and planning measurements for a better prioritization over vast areas of potential locust habitats. The final research questions addressing in the context of this objective are formulated as:

Research Questions 4:

- How can different types of geospatial and remote sensing datasets be simplified for a straightforward spatial analysis?
- How can expert rules, applied in practice, be implemented to exploit geospatial and remote sensing datasets?
- What kind of practical locust management tasks can be conducted by such spatial applications?

1.4 Thesis structure

This dissertation is structured in seven main chapters. In chapter one, an introduction of the multidisciplinary topic “locust” and requirements on modern locust management and the role of remote sensing are presented. Additionally, chapter one provides the principles, objectives, research questions and structure of this thesis. In chapter two, the reader is provided with a synthesized description of the main biological and ecological characteristics of locusts in general, as well as the threat of locust plagues and outbreaks nowadays. The main body of the research is presented in chapters three to seven, whereby chapters three, four, five and six are organized and presented in the form of individual research articles, which have been published or submitted to peer-reviewed scientific journals.

Chapter three focuses on a comprehensive review of existing studies, which apply remote sensing datasets for locust research and management. This review study examines which locust species and regions of interest were focused on, applied methods and remote sensing datasets which were implemented under the aspect of spatial and temporal resolution and their main objectives. The review study was essential for further research of this thesis because it allowed the identification of research gaps and formed the basis for further method development and appropriate data selection for all subsequent applications. The content of this chapter was published in the following journal:

Klein, I., Oppelt, N. & Kuenzer, C. (2021). Application of Remote Sensing Data for Locust Research and Management - A Review. Insects, 12, 233. https://doi.org/10.3390/insects12030233.

In chapter four, remote sensing data in combination with different geospatial environmental datasets and individual species-relevant parameters, are used to model the suitability of areas for successful eggs survival and locust breeding. The application is performed within ENM and HSI models for three different locust species and three different regions of interest to demonstrate the advantage of higher spatial resolution data, as well as the importance to consider species-relevant features and ecological characteristics. The research presented in this chapter was published in:

Klein, I., van der Woude, S., Schwarzenbacher, F., Muratova, N., Slagter, B., Malakhov, D., Oppelt, N., Kuenzer, C. (2022). Predicting suitable breeding areas for different locust species - A multi-scale approach accounting for environmental conditions and current land cover situation. International Journal of Applied Earth Observation and Geoinformation, 107, 02672. https://doi.org/10.1016/j.jag.2021.102672.

Chapter five presents how remote sensing and up-to-date information on the land cover situation can contribute to future locust management and preventive measurements. In this study, the relation between Moroccan locust breeding sites of the recent outbreak in Sardinia, Italy, and abandoned or fallow land is quantified. The study described in this chapter is submitted and will be likely published in:

Klein, I., Cocco, A., Uereyen, S., Mannu, R., Ignazio, F., Oppelt, N., Kuenzer, C. (2022). Outbreak of Moroccan locust in Sardinia (Italy): A remote sensing perspective. Remote Sensing, 14(23), 6050. https://doi.org/10.3390/rs14236050.

In chapter six, the application of remote sensing and geospatial datasets is presented in a standardized h3-hexagon system to simplify application and analyses for locust managers and field teams. The study focuses on how available geospatial information can be exploited based on a practical example case from Italian locust in Pavlodar region (Kazakhstan). The study described in this chapter is submitted and will be likely published in:

Klein, I., Uereyen, S., Eisfelder, C., Pankov, V., Oppelt, N., Kuenzer, C. (2023). Application of geospatial and remote sensing data to support locust management. International Journal of Applied Earth Observation and Geoinformation, 117, 103212. https://doi.org/10.1016/j.jag.2023.103212.

Finally, chapter seven provides the reader with a synthesized summary of the results and answers formulated research questions obtained from chapter three to six. Furthermore, future research challenges and opportunities in the field of locust research and management with the inclusion of remote sensing applications are addressed.

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CHAPTER 2

2 Key aspects of locust ecology

Locusts belong to the group of grasshoppers of the family *Acridoidea*. However, locusts differ from grasshoppers because of their capability to change their behavior and appear in two different phases depending on their population density (Cullen et al., 2017; van Huis, 2021). This so-called locust phase polyphenism is characteristic for locust species. At low population density locusts are solitarious*,* behave as individuals and avoid each other (Le Gall et al., 2019; Zhang et al., 2019). In this phase, they stimulate plant growth, participate in nutrient cycling and are important component of food chains and grassland ecosystems (Latchininsky et al., 2011). However, once the population of locusts is increasing and reach a high density, the phase changes and locusts become gregarious. During the gregarious phase locusts behave in crowds, form bands during hopper stages and swarms after fledgling. Swarms invade large territories and cause devastation in agricultural production and pasture (Sword et al., 2010). Outbreaks of locusts and grasshoppers can be either chronic (e.g., grasshopper species in the African Sahel, China) or episodic (e.g., desert locust, Australian plague locust, South American locust, Migratory locust). For species with episodic outbreak character, time development can be considered as periods of invasion and recession (Zhang et al., 2019). For more information on locust phase change the reader is referred to e.g., Buhl and Rogers (2016), Pener and Simpson (2009), Uvarov (1977), Wang and Kang (2014).

2.1 Locust life cycle

The locust life cycle can be categorized in a succession of three stages: egg, nymph (in some literature also referred to as instar, hopper or, larvae) and adult. Locust species in temperate regions, such as CIT and DMA are univoltine. This means they produce one generation per year and the eggs remain in diapause during winter. Nevertheless, population density can increase rapidly from year to year during favorable environmental conditions, and sometimes in combination with anthropogenic factors. Tropical and subtropical species such as desert locust and Australian plague locust can produce two to four generations per year depending on meteorological conditions (Latchininsky, 2013; Steedman, 1990; Uvarov, 1977). A typical locust life cycle of univoltine species is illustrated in Figure 2-1.

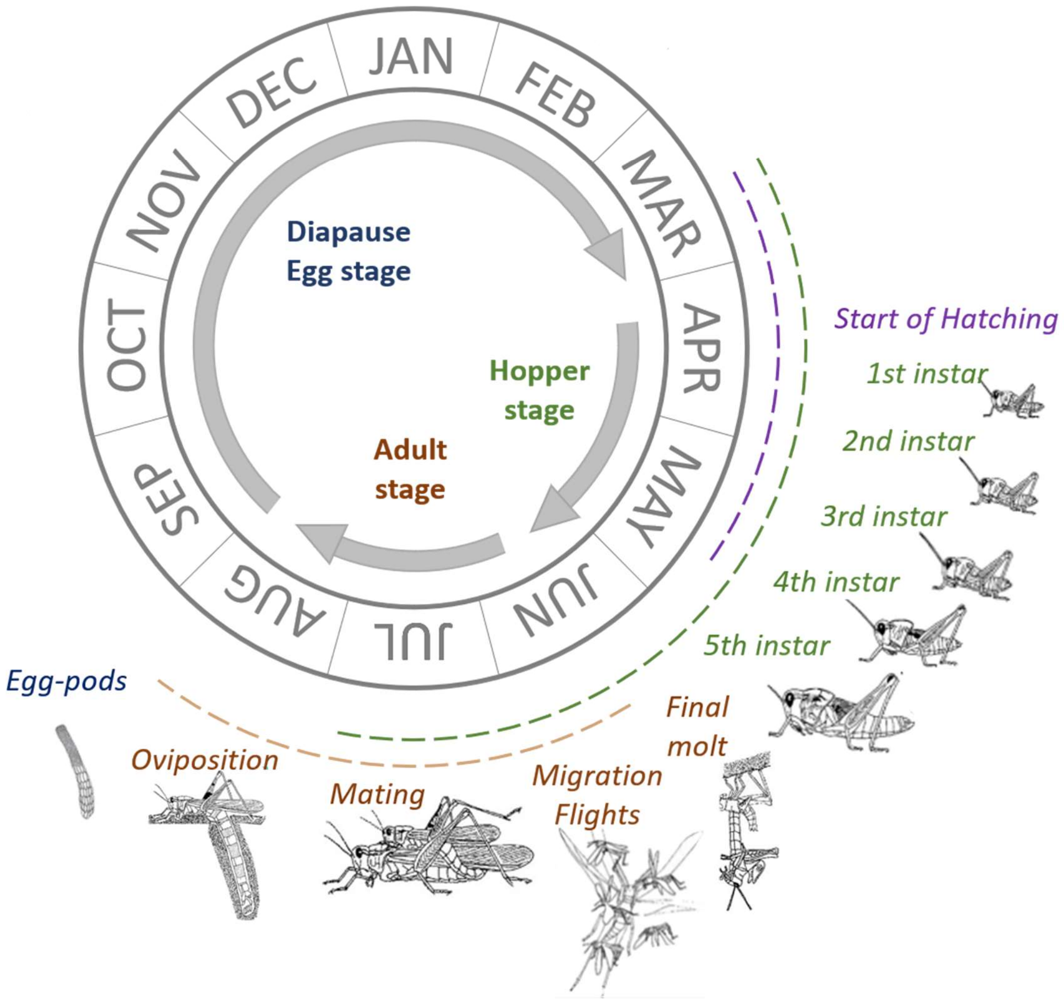

Figure 2-1. Exemplary life cycle of univoltine locust species (Northern hemisphere). Adjusted based on Latchininsky (2013). Exact timing and duration of stages are determined by geographical location, species and meteorological conditions.

The eggs laid by female insects are preserved within a so called egg pod (Figure 2-2) which can contain from 30 to over 100 eggs depending on the species (Latchininsky, 2013). Hatching of the eggs usually occurs after certain environmental conditions are met (e.g., soil moisture, temperature). After hatching, locust undergo five to seven successive hopper stages (Figure 2-3, 2-4) to finally become adult insects capable of flying. Each hopper stage lasts approximately from three to eight days depending on meteorological conditions and food availability (Sergeev et al., 2022; Uvarov, 1977). While, higher temperature usually leads to faster development. After fledgling (last molt), locusts are capable to fly, become mature and can migrate large distances. The migration distances depend again on locust species and meteorological conditions and may vary daily from 10 km for DMA up to 200 km or even 1000 km especially for desert and migratory locusts during extreme events (Latchininsky, 2013; Steedman, 1990). The capacity of long distance migration is an additional aspect making locusts extremely dangerous transboundary pests (Latchininsky, 2013; Uvarov, 1977). Finally, mature adults mate and lay their eggs (Figure 2-5, 2-6). The period between mating and laying e.g. for CIT is between 3 to 5 days (Sergeev et al., 2022). One individual female can lay one to four egg pods. Therefore, during gregarious phase the density of egg pods can reach up to several thousand per m². In total, the life spam of locusts depends mainly on the time it takes to become sexually mature, which can last from 2.5 to 5 months (Steedman, 1990). For more information on different locust species, their distribution and ecological specification the reader is referred to e.g., COPR (1982), Le Gall et al. (2019), Steedman (1990).

Figure 2-2. Italian locust egg pod (Photo: Kazakhstan, Pavlodar region, July 2022).

Figure 2-3. Second phase hoppers of Moroccan locust (Photo: Kazakhstan, Turkistan region, April 2019).

Figure 2-4. First and second phase hoppers of Moroccan locust (Photo: Italy, Sardinia, April 2022, © Arturo Cocco).

Figure 2-5. Italian locust during mating (Photo: Kazakhstan, Pavlodar region, July 2022).

Figure 2-6. Italian locust females during oviposition (Photo: Kazakhstan, Pavlodar region, July 2022).

2.2 Main characteristics and distribution of the Italian locust

2.2.1 Environmental and ecological factors

In year 1008 the first recorded great pest in Russia was caused by CIT (FAO, 2021). Although CIT is on the red list of endangered species in northern Europe, it is a threatening acridid pest in the steppes and semi-deserts of Siberia, Central Asia and the Caucasus (Latchininsky, 2013; Sergeev, 2021; Sergeev and Van'kova, 2008). The distribution of CIT ranges from Europe to the southern part of West Siberia, East Kazakhstan, and North-West China (Figure 2-7). Within this large territory, preferred habitats can be found in heterogeneous semi-arid landscapes containing vegetation types dominated by wormwood and sagebrush (*Artemisia spp.*, (Monard et al., 2009; Sergeev, 2021)). This kind of vegetation compositions can be also found in some human-affected areas such as field borders, fallow fields, neglected orchards, waste lands and road edges (Kambulin, 2018; Latchininsky, 2013; Sergeev et al., 2022). CIT tolerates a wide range of semi-arid soils and climate conditions (Monard et al., 2009). However, during periods between outbreaks, it is observed that CIT prefers very dry habitats in the north of its distribution range. In the central parts it prefers relatively dry and diverse habitats of the steppe and semi-desert and meadow habitats of river valleys or in mountains in the southern parts (Sergeev, 2021). CIT disappears completely due to mechanical destruction of egg pods when land is tilled. Besides food preference, the occurrence of CIT is related to physical soil properties. Moderate compact sandy soils are more favorable than very loose or compact soils and thus facilitating oviposition (Toleubayev et al., 2007).

CIT is a typical univoltine species (Figure 2-1). Once moisture is introduced during the warming period in spring, the incubation period starts and hatching occurs from late April to June. During this period, higher temperatures and lower precipitation generally lead to increased survival and thus higher population. Therefore, once ecological conditions are highly suitable over a multiple-year period, a high density of egg pods and increased survival rates cause higher density of adult individuals. In case there are no control measurements during this upsurge periods, the population upsurge leads to outbreaks (Sergeev and Van'kova, 2008). CIT is an intermediate form between gregarious and solitarious species with migration distances of several hundred meters for bands and 100-200 km for swarms (Sergeev, 2021). However, during extreme events, swarms can migrate up to 750-800 km. During outbreaks they can colonize all kind of fields and transformed habitats. If available, CIT prefers to consume dicotyledon plants and therefore can seriously damage different types of crops (Sergeev, 2021).

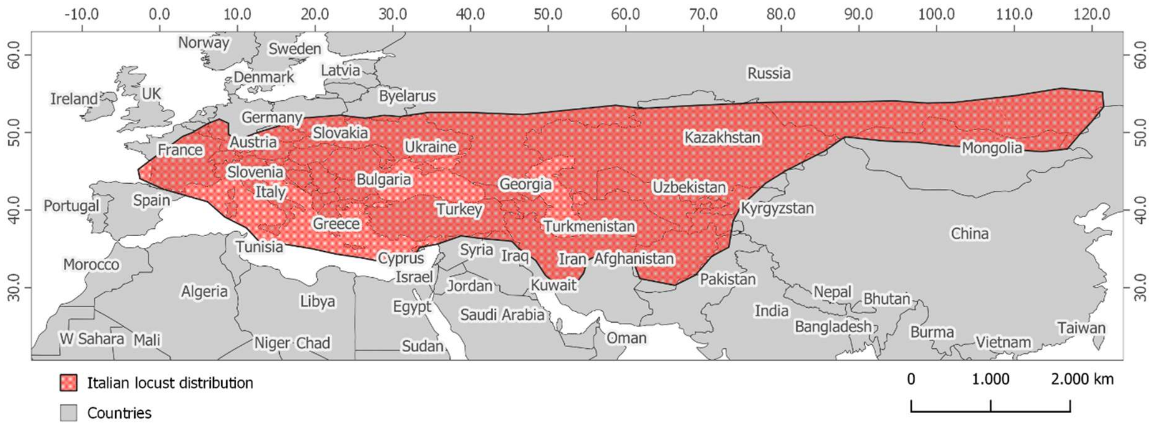

Figure 2-7. Italian locust distribution (adjusted based on FAO (2021)).

2.2.2 Plagues and outbreaks

Population upsurge of locust and resulting outbreaks show a regular rhythm which is related to sun activity (sunspots cycle of eleven years) and intervals of approximately nine to twelve years. After the maximum of sun activity, locust population usually starts to increase.

Between 1940 and 1990 outbreaks of CIT occurred mostly on local scale without infestation of large territory but with regular occurrences and serious consequences for affected regions and local livelihoods. In the southern part of Western Siberia, four outbreaks were documented in 1952-1956, 1967-1971, 1977-1982, and 1999-2002 and in North Caucasus and lower Volga the outbreaks occurred slightly later in 1954-1957, 1972-1974, 1982-1984, and 1992-1998 (Sergeev, 2021). The last and worst outbreak started in 1991 in North Caucasus and lower Volga region and spread from year-to-year eastwards towards Kazakhstan (1996-1998), reaching finally a peak outbreak between 1999-2001 in eastern and northern parts of Kazakhstan. A total of eight Mio. ha of infested land had to be treated by chemical control activities. The outbreak was qualified as a plague because of the large scale infection and duration over several years (Sergeev and Van'kova, 2008). The reasons of this plague were also due to economic transformation in the former USSR countries as plant protection organizations were partly out of order and had limited transboundary communication between countries. At the same time, large areas with abandoned fields provided optimal conditions for locust breeding and population increase. Since then, sporadic outbreaks were located in central and eastern parts of CIT range but has been controlled immediately by better organization and structures of affected regions (Sergeev, 2021). For more detailed description of CIT and its outbreaks the reader is referred to Sergeev et al. (2016, 2022).

2.3 Main characteristics and distribution of the Moroccan locust

2.3.1 Environmental and ecological factors

Previously, DMA was considered as one of the most dangerous agricultural pests in the Mediterranean zone and Central Asia. However, the population of this species has decreased and is highly fragmented due to industrial, agricultural and urban developments and accompanied transition of natural habitats (Latchininsky, 1998). Nevertheless, DMA still leads to outbreaks and damages in crops and pasture especially in Central Asia. The habitats of DMA are distributed ranging from Atlantic islands in the west, through Mediterranean zone, Caucasus, Central Asia and Afghanistan in the east (Figure 2-8). The permanent breeding hotspots are isolated during low population densities (Latchininsky, 1998).

On the contrary to CIT, DMA has quite specific requirements for suitable breeding areas. Preferred habitats are located in elevated regions and foothills at altitudes of 400-800 m above sea level with hard dry soils, high clay content and ephemeral spring forbs (Latchininsky, 1998; Monard et al., 2009). The annual precipitation varies between 300-500 mm, whereby spring precipitation specifically, being the most important for development at optimum around 100 mm (Kokanova, 2017). Preferred breeding areas are found within mosaics of steppe vegetation and bare soils, typically for overgrazed pasture. The degree of overgrazing and tramping by cattle play an important role to create vegetation mosaics and compact soil which are ideal breeding and gregarization milieu for DMA (Latchininsky, 1998). Similar to CIT, agricultural activity usually destroys egg pods. Furthermore, dense vegetation, no vegetation at all, wet and moist areas are unsuitable for DMA breeding (Latchininsky, 1998, 2013; Uvarov, 1977; Zhang et al., 2019).

The DMA is also an univoltine species with winter egg diapause (Figure 2-1). Hatching takes place from February to April including successive five hopper stages. The migration distances during outbreaks reaches between 70-100 km which is quite short when compared to other locusts pests' (Latchininsky, 1998).

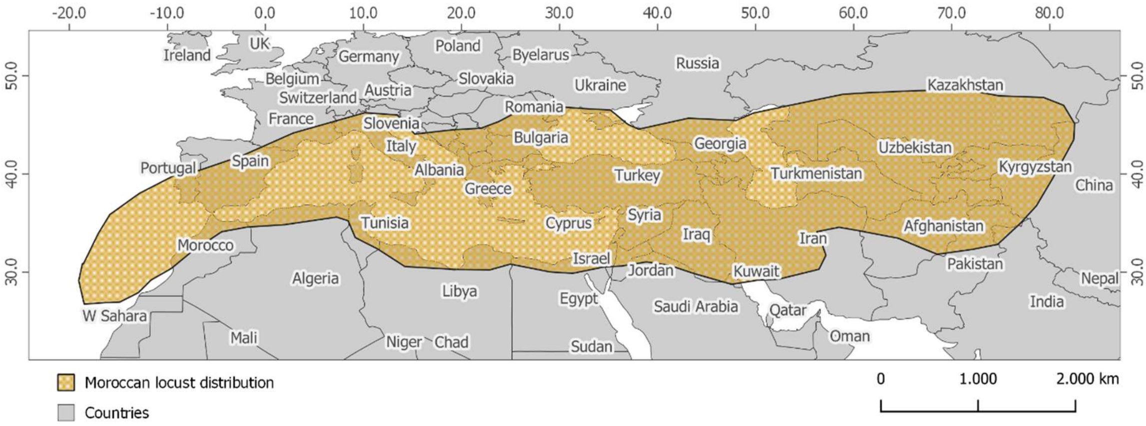

Figure 2-8. Moroccan locust distribution (adjusted based on FAO (2021)).

2.3.2 Plagues and outbreaks

According to Latchininsky (1998) the actual state of DMA differs significantly depending on location and human practice. For example, in continental France DMA does not produce swarms because its habitat has significantly shrunk due to agricultural activities. On the contrary, in Spain, vast and continuous zone of native dry grasslands still exists. Therefore, monitoring and chemical control activities are necessary to maintain the population low. In 1983 a total of 130.657 ha and in 1992 113.600 ha were infested in Spain. Further main outbreaks are documented for Hungary (1948-1949, 1993), Bulgaria (1939-1940), and Balkan region (1930-1933). Many of these outbreaks are considered to be a result of increased fallow fields, which provided areas for locust population upsurge, in combination with prolonged droughts around those times. Particular wars and political instability leading to collapse of agricultural activities and consequently abandoned fields, played a major role for many DMA related outbreaks (Latchininsky, 1998). Regular outbreaks in Sardinia (1932-1934, 1946, 1951, 1988-1989, 2019-2022), North Africa, and all Central Asian countries are still common until present days and requires continuous monitoring and phytosanitary control activities to maintain the population low. Furthermore, DMA is a major pest in Near East with harmful plagues in West Anatoliea, Mesopotamia and Southern Caucasus (Ciplak 2021). For more detailed description of DMA and its outbreaks the reader is referred to Benfekih et al. (2002), Kokanova (2017), Latchininsky (1998), Molinu et al. (2004), Uvarov (1957).

2.4 Other locust species

There are about 25 species around the world which are considered to be major pest locusts (Lecoq and Cease, 2022). The most distributed locust species is the migratory locust and its many subspecies (Figure 2-9). The migratory locust is present across entire temperate and tropical Eastern hemisphere (Le Gall et al., 2019). Plagues are associated with droughts and flood events because their habitats are distributed typically around rivers, lakes and deltas covered with plantings of reeds and sedges.

Furthermore, the most dangerous migratory agricultural pest is the desert locust (*Schistocerca gregaria*) (Cressman, 2016). Its distribution is found in deserts of North Africa, the Middle East and Southwest Asia covering approximately 16 Mio. km² of recession area (Cressman, 2016). Outbreaks and plagues of desert locust cover large areas with massive crop losses. For example, during 2003-2005 outbreak in West Africa a total of 13 Mio. ha were treated with broad-spectrum insecticides across 22 countries (Cressman, 2016). During the most recent outbreak in the Horn of Africa, a total of 2.2 Mio. ha were treated since march 2020 (FAO, 2022). The distribution of desert locust and some other important destructive locust species are presented in (Figure 2-10).

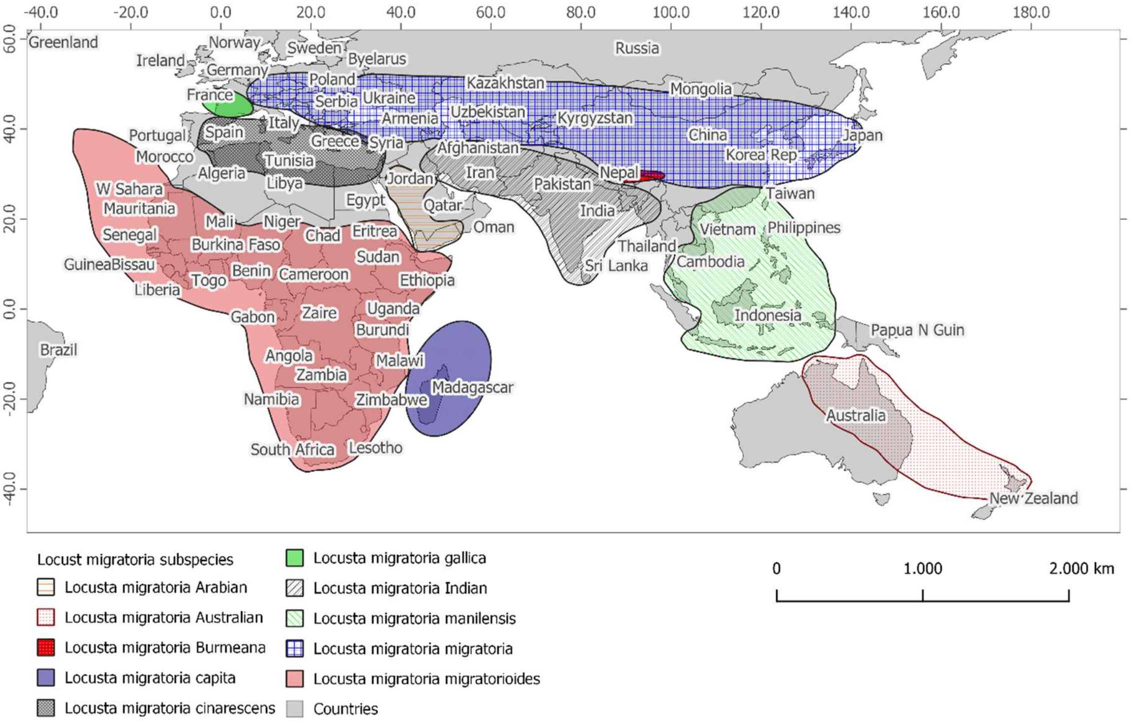

Figure 2-9. Locust migratoria subspecies distribution (adjusted based on Steedman (1990)).

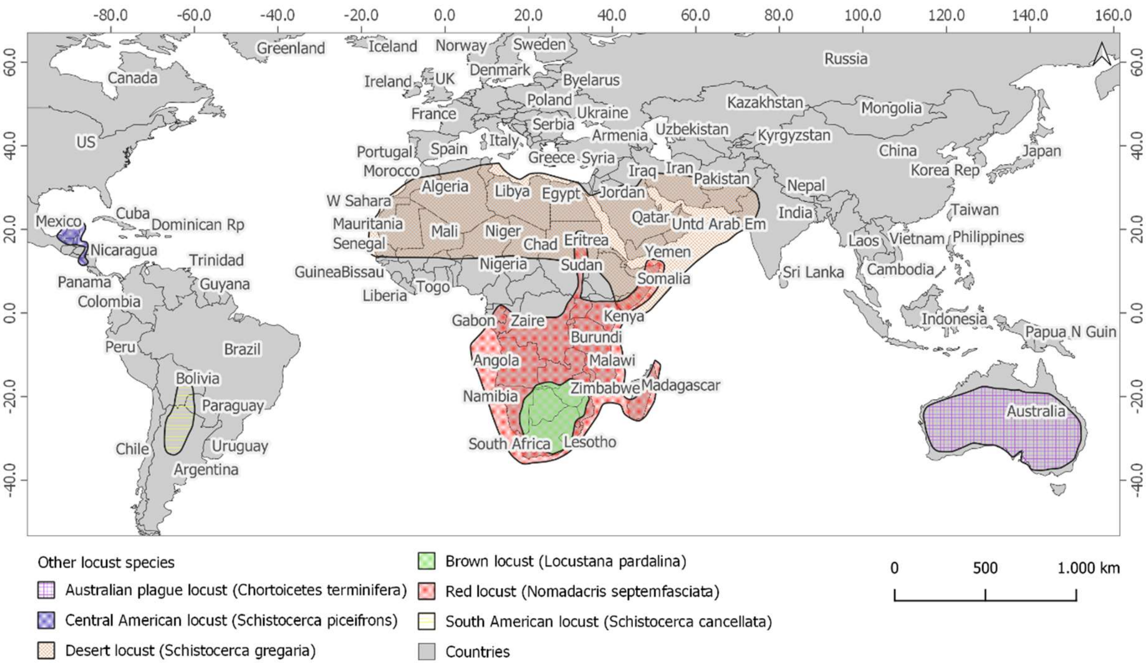

Figure 2-10. Additional locust species distribution (adjusted based on Latchininsky (2013), Lecoq (1995), Steedman (1990), Trumper et al. (2022)). Not included species e.g., Bombay locust, Javanese grasshopper, Mongolian locust, Peruvian locust, rangeland grasshopper, rice grasshopper, Sahelian grasshoppers, Senegalese locust, Siberian locust, Spur throated locust, Sudan plague locust, tree locusts, variegated grasshopper. For more information and complete overview, the reader is referred to COPR (1982), Le Gall et al. (2019), Steedman (1990).

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CHAPTER 3

3 Application of remote sensing data for locust research and management – A review

Abstract

Recently, locust outbreaks around the world have destroyed agricultural and natural vegetation and caused massive damage endangering food security. Unusual heavy rainfalls in habitats of the desert locust (Schistocerca gregaria) and lack of monitoring due to political conflicts or inaccessibility of those habitats lead to massive desert locust outbreaks and swarms migrating over the Arabian Peninsula, East Africa, India and Pakistan. At the same time, swarms of the Moroccan locust (Dociostaurus maroccanus) in some Central Asian countries and swarms of the Italian locust (Calliptamus italicus) in Russia and China destroyed crops despite developed and ongoing monitoring and control measurements. These recent events underline that the risk and damage caused by locust pests is as present as ever and affects 100 million of human lives despite technical progress in locust monitoring, prediction and control approaches. Remote sensing has become one of the most important data sources in locust management. Since the 1980s, remote sensing data and applications have accompanied many locust management activities and contributed to an improved and more effective control of locust outbreaks and plagues. Recently, open-access remote sensing data archives as well as progress in cloud computing provide unprecedented opportunity for remote sensing-based locust management and research. Additionally, unmanned aerial vehicle (UAV) systems bring up new prospects for a more effective and faster locust control. Nevertheless, the full capacity of available remote sensing applications and possibilities have not been exploited yet. This review paper provides a comprehensive and quantitative overview of international research articles focusing on remote sensing application for locust management and research. We reviewed 110 articles published over the last four decades, and categorized them into different aspects and main research topics to summarize achievements and gaps for further research and application development. The results reveal a strong focus on three species—the desert locust, the migratory locust (Locusta migratoria), and the Australian plague locust (Chortoicetes terminifera)—and corresponding regions of interest. There is still a lack of international studies for other pest species such as the Italian locust, the Moroccan locust, the Central American locust (Schistocerca piceifrons), the South American locust (Schistocerca cancellata), the brown locust (Locustana pardalina) and the red locust (Nomadacris septemfasciata). In terms of applied sensors, most studies utilized Advanced Very-High-Resolution Radiometer (AVHRR), Satellite Pour l'Observation de la Terre VEGETATION (SPOT-VGT), MODIS as well as Landsat data focusing mainly on vegetation monitoring or land cover mapping. Application of geomorphological metrics as well as radar-based soil moisture data is comparably rare despite previous acknowledgement of their importance for locust outbreaks. Despite great advance and usage of available remote sensing resources, we identify several gaps and potential for future research to further improve the understanding and capacities of the use of remote sensing in supporting locust outbreak- research and management.

3.1 Introduction

Locust and grasshopper pests have been destroying agriculture and affecting human lives by causing major food security challenges since ancient times and serious outbreaks are documented both in historical sources and modern literature (Gupta, 1983; Huang et al., 2016; Le Gall et al., 2019; Zhang et al., 2019). There are approximately one dozen serious pest locust and grasshopper species, which are capable of migrating great distances and are destructive to crops, pastures and other green vegetation during their gregarious phase (Kimathi et al., 2020; Steedman, 1990). Locusts differ from other insects because their population can grow rapidly, forming dense bands and swarms (Zhang et al., 2019). In the solitarious phase, locusts are an important part of ecosystems. However, a change in environmental conditions and growth in population may initiate the gregarious phase, which can lead to an outbreak (Zhang et al., 2019). Furthermore, locust population dynamics are also influenced by land management (Cease et al., 2015). For locust phase polyphenism and population density research, we refer the reader to (Cullen et al., 2017; Sergeev and Van'kova, 2008; Sword et al., 2010; Xiang et al., 2016).
One of the most destructive species, the desert locust (*Schistocerca gregaria*), is responsible for the most dramatic and sudden outbreaks and plagues in the 20th and 21st centuries (Pedgley, 1981; Zhang et al., 2019). Low populations of the desert locust are usually present at any time across a vast recession area of 16 Mio. km², stretching from West Africa to Southwest Asia (Cressman, 2013). Migrating downwind, the desert locust breed sequentially where winter, spring and summer rains are falling (van Huis et al., 2007). Warm weather conditions and unusual heavy rainfalls combined with a lack of monitoring created perfect conditions for the recent 2019/2020 outbreak, which was evident in large occupied areas across East African countries, the Arabian Peninsula, Pakistan and India (Roussi, 2020). Apart from desert locust outbreaks, there were local outbreak occurrences of the Moroccan locust (*Dociostaurus maroccanus*) in parts of Central Asia, the Italian locust (*Calliptamus italicus*) in parts of East Russia, the South American locust (*Schistocerca cancellata*) in parts of Paraguay and Argentina, the African migratory locust (*Locusta migratoria migratorioides*) in Botswana, Namibia, Zambia and Zimbabwe as well as Yellow-spined bamboo locust (*Ceracris kiangsu*) in parts of Vietnam, Laos and China (Arizona State University, 2020). Furthermore, an unexpected Moroccan locust outbreak during summer 2019 and 2020 destroyed several thousand hectares of crops in Sardinia, Italy (Reuters, 2019). These recent large-scale as well as local outbreak events of different locust species around the world underline the actual presence of locust pest risk for food security, their destructive effects and the importance of functioning locust management services.

Outbreaks of locust and grasshopper are either chronic (e.g., grasshoppers in the African Sahel and grasshoppers/locusts in China) or episodic, with alternating periods of invasion and recession (e.g., the Australian plague locust and the desert locust) (Zhang et al., 2019). Locust outbreaks have many negative effects on land management, food security and the natural environment, ranging from total damage of crops and grazing fields to negative effects from control measurements when using insecticides. In Figure 3-1, we summarize general effects of locust outbreaks. In particular, the damage to crops and chemical contamination caused by control measurements have short- to long-term negative impacts (Prior and Streett, 1997; Zhang et al., 2019).

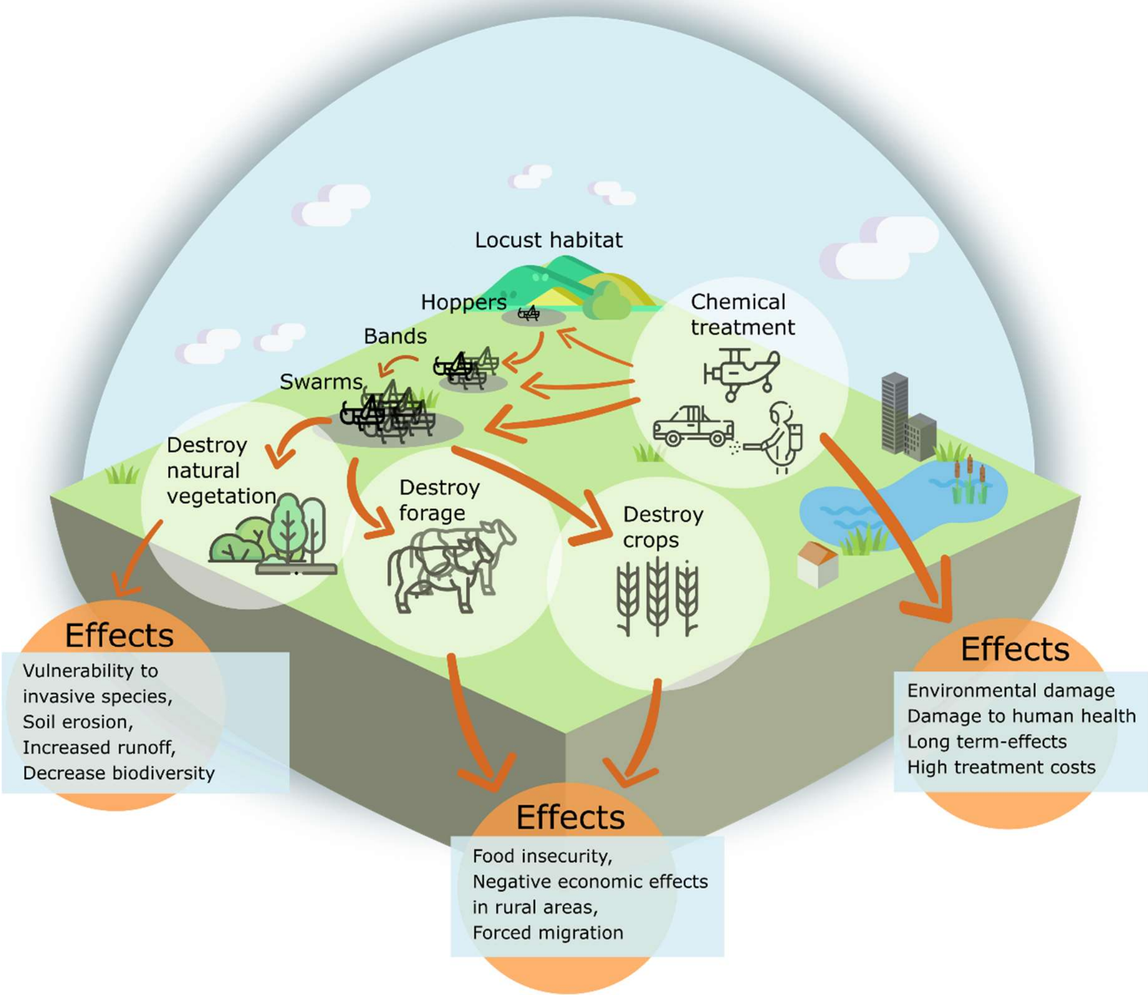

Figure 3-1. Schematic sketch of locust interaction during the gregarious phase (outbreak) with the natural environment, agriculture and human settlements.

Due to the size of the impact, locust management and control are essential. Locust management is complex and requires a multi-disciplinary approach including entomology, biology, and ecology, with aspects of spatial distribution modelling, climate analysis, weather prediction, organism behavior and interaction with other species (e.g., birds and grazing sheep), control using chemical insecticides or bio-agents as well as remote sensing applications. The latter has become one of the most important sources providing valuable information within locust management. Meanwhile, there is a wide range of existing passive (employ natural sources of energy) and active (emit a controlled beam of energy and detect the amount of energy reflected back to the sensor) Earth Observation (EO) sensor systems. For a detailed introduction to remote sensing, we refer the reader to (Chuvieco, 2020; Lillesand et al., 2015; Schowengerdt, 2007). The most important sensor characteristics are the spectral resolution (number of spectral bands), spatial resolution (smallest unit-area indicating the minimum size of objects that can be detected), temporal resolution (time between two observations of one and the same location) and spatial coverage (total area covered by one image). For this review, important sensor types can be categorized into optical sensors (covering visible, near infrared (NIR), short-wave infrared (SWIR) spectrum) and sensors covering thermal infrared (TIR). Spaceborne radar (RAdio Detection and Ranging) remote sensing includes passive and active systems. While active sensors are usually characterized by higher-spatial-resolution, passive microwave sensors operate on coarser resolution (Ottinger and Kuenzer, 2020). The electromagnetic radiation spectrum with important bands used in satellite remote sensing (SRS) is shown in Figure 3-2.

Remote sensing-based research and case study applications were important drivers to improve our understanding of locust-relevant ecological and environmental conditions. Since the 1980s, information acquired from remote sensing data has accompanied many locust management activities and contributed to improved and more effective control of locust outbreaks and plagues around the world. Nevertheless, locust outbreaks still cause devastation and hunger, despite technological progress and improvement in monitoring and control. One of the reasons is the ineffective monitoring, management or population control in some locust habitats, e.g., due to lack of available resources and technology (Roussi, 2020). Environmental changes (e.g., land use alterations) and weather variability within the locust habitats can create optimal conditions for locust breeding, which needs to be realized and control undertaken in time. Otherwise, such changes may lead to increased population, causing a transition from the solitarious phase to the gregarious phase and therefore initiate a locust outbreak. Therefore, continuous monitoring during the solitarious phase is essential. Apart from short- to mid-term variability of important ecological variables, the effect of climate change is also considered to be a factor for more frequent and severe outbreaks (Meynard et al., 2020; Salih et al., 2020; Tratalos et al., 2010).

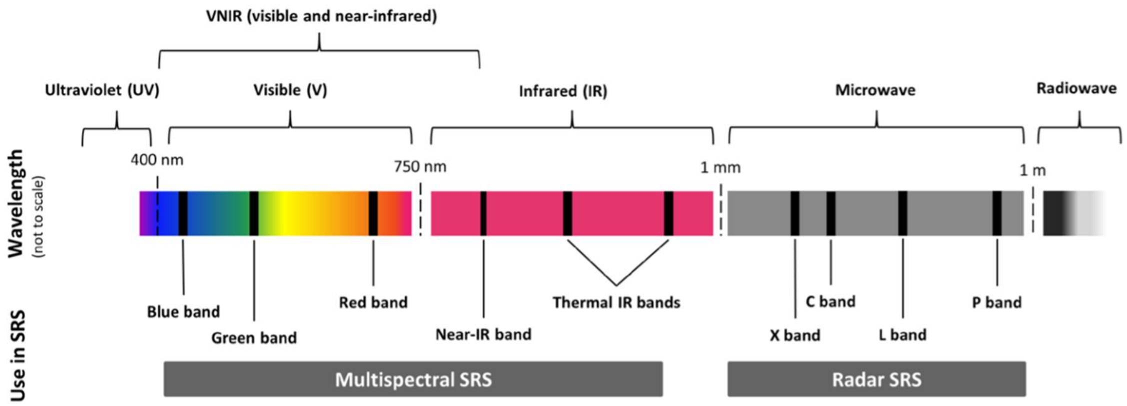

Figure 3-2. Electromagnetic radiation spectrum with bands used in satellite remote sensing (SRS) from Pettorelli et al. (2018).

The Food and Agriculture Organization (FAO) has been successfully introducing standardized monitoring methods and data collection when remote sensing data and applications play an essential role. Remote sensing data related to locust outbreaks was first introduced by Pedgley (1974) and Hielkema (1977) and was later implemented in FAO operative desert Locust Information Service (DLIS). Hielkema et al. (1990) and Hielkema and Snijders (1994) focused on Meteosat cloud imagery to estimate rainfall, and on Landsat and AVHRR-based estimation of vegetation development. The Australian Plague Locust Commission (APLC) is another organization successfully utilizing remote sensing data to support locust management (Bryceson, 1990; Hunter, 2004). Since then, FAO and APLC and different research projects have contributed to a steady progress in implementing remote sensing-based products. In general, remote sensing can provide different kinds of information at different critical moments within the locust life cycle. Figure 3-3 represents a typical locust life cycle and sketches where remote sensing technologies have been applied in the past and present or have the potential for future applications. These applications can be summed up in following overarching topics:

- Mapping and monitoring the locust habitat state and environmental conditions which promote the transition process between the solitarious and gregarious phases.
- Prediction of hatching time and possible outbreaks based on historical information, present vegetation monitoring and weather forecast.
- Locust nymph bands and swarm monitoring with airborne or UAV-based sensors.
- Post outbreak crop and vegetation damage assessment.
- In addition to EO remote sensing, direct radar (X-band) observations of ‘migration in progress’ have been used for research on the migration systems of locusts and migratory grasshoppers, particularly for the Australian Plague locust and the Senegalese grasshopper (Drake and Reynolds, 2012). Insect-monitoring radars (IMRs) are currently used to supplement existing survey and monitoring programs of the Australian Plague locust (Drake and Wang, 2013).

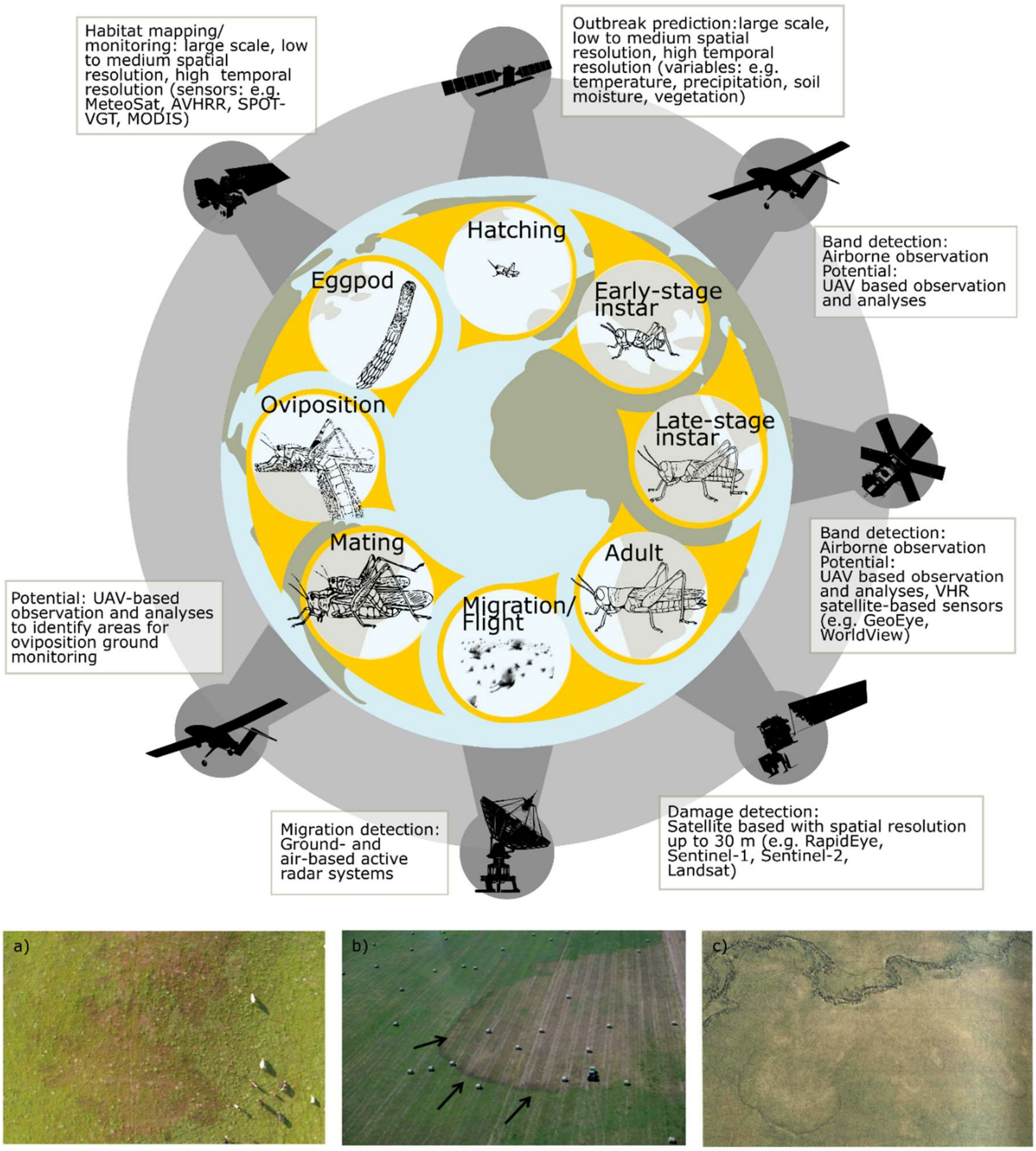

Figure 3-3. Representative life cycle of locust and grasshopper species including critical phases for locust management and where remote sensing can provide support and provide data.
a) Red, green, blue (RGB) image taken by a UAV from 80 m height with visible vegetation damage caused by early stage of the Moroccan locust (South Kazakhstan, April 2019). b) Aerial image of bands of the Australian plague locust and visible caused damage (source: Figure 60 from Weiss, (2016), photos from Victorian Government Agriculture Department). c) Bands of the Australian plague locust and damaged vegetation visible in airplane-taken RGB image from 400 m height (source: Figure 2 from Hunter et al. (2008)).

This review aims to provide a comprehensive and quantitative overview on ‘satellite-based’ remote sensing applications and research within critical phases for locust management. Due to high potential for locust management, as well as similar principles in image interpretation and processing, we also included UAV and airborne-based studies. We aim to summarize past and present developments and identify topics which still require further research and scientific attention. This review is structured as follows: in Section 2. Materials and Methods, we present the applied literature search and categorize different publication-specific aspects and thematic foci which are reviewed and presented separately. In Section 3. Results, we present the outcome for each aspect and summarize most important findings. In Section 4. Discussion, results are critically discussed, gaps and further potential are stated. In Section 5. Conclusion, we summarize and underline main findings.

3.2 Materials and methods

Locust pest research and management cover several scientific disciplines. Therefore, potential articles cover a broad range of journals. For this review, we systematically reviewed 110 scientific publications including remote sensing applications which were published since 1980. The conducted literature search was based on the bibliographic digital database of Web of Science (last accessed on 15 December 2020) including Science Citation Index (SCI) journals and full-text conference contributions (Figure 3-4). For the literature search, we used specified terms and additional keywords including ’locust’, ’locust pest’, ’locust plague’, ’locust outbreak’ and ‘grasshopper’ in combination with ’remote sensing’ or ‘satellite’, ‘UAV’, ‘airborne’ as well as ’habitat’, ‘monitoring’, ‘prediction’, ‘control’, and ‘management’. This search query resulted in a very large number of research articles also including publications which are not related to locusts and grasshoppers (Orthoptera: Acrididae). Therefore, additional excluding keywords were applied. In a final step, we screened the resulting publications based on the following inclusion criteria which are relevant for this review:

- Articles are related to locust and grasshopper species (Orthoptera: Acrididae).
- Articles should be based or include EO, airborne or UAV data as one of the data sources.
- Articles investigated either locust/grasshopper habitat, presence, or outbreak prediction.
- Articles are related to locust/grasshopper ecological modelling or population distribution with EO-based input.
- Articles related to locust/grasshopper damage monitoring/mapping with EO.
- The literature review workflow and number of studies for each step are summarized in Figure 3-4.

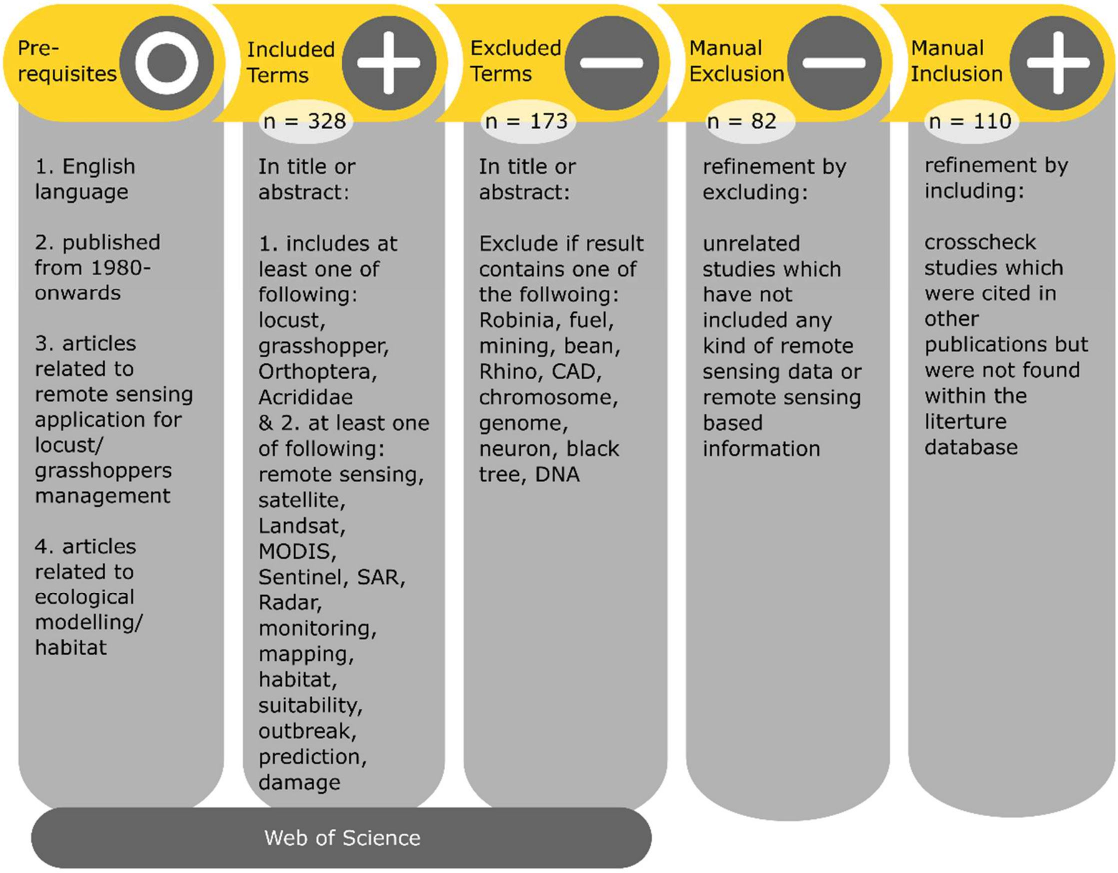

Figure 3-4. Workflow and literature searching criteria applied for this review.

The total selected 110 studies were analyzed to extract relevant information for this review in two main aspects. The first aspect includes publication-specific information about “species of interest”, “region of interest”, “applied remote sensing sensor” and “derived variables from remote sensing data”. Additionally, we extracted involved authors’ affiliation to investigate where main research is based compared to regions of interest. The second aspect includes thematical foci which were categorized into “habitat mapping”, “habitat monitoring”, “forecast of hatching/outbreak”, “damage assessment” as well as “review and general articles” without a specific data analyzing part (Table 3-1).

Table 3-1. Categorization of research articles for this review.

Publication-Specific Aspects	Thematic Foci
Species of interest	Habitat mapping (static)
Region of interest (country level)	Habitat monitoring (temporal)
Sensor and used variables, scales	Outbreak/Hatching prediction (future)
Authors’ affiliation (country level)	Damage assessment (past)
	Review articles (general)

3.3 Results

3.3.1 Development over time

In this section, we recap the historical development of studies related to locust research and management applying remote sensing data (Figure 3-5). The first studies were published by Pedgley (1974) and Hielkema (1977) using Landsat Multi-Spectral Scanner (MSS) data to detect the presence of green vegetation in desert locust habitats in northwest Africa. After recognizing the potential of satellite imagery, the 1980s and 1990s were dominated by a few experimental studies and pioneer research on how remote sensing data analysis and application could be utilized to provide valuable information for locust management and to be implemented into operational services. Referring to locust plagues, Hielkema (1981) introduced satellite remote sensing for desert locust habitat monitoring as “a new technology to an old problem”. McCulloch and Hunter (1983), Bryceson and Wright (1986), Bryceson and Bryceson (1989, 1990, 1991) and Bryceson et al. (1993) investigated the usage of Landsat MSS imagery to identify and monitor habitats of the Australian plague locust. Tucker et al. (1985) introduced the potential of AVHRR and Landsat datasets to forecast desert locust activity. Further feasibility studies followed for the Senegalese grasshopper (*Oedaleus senegalensis*) (Tappan et al., 1991, 1990; Tappan and Moore, 1989), the brown locust (Nailand, 1993), and the Moroccan locust (Latchininsky, 1998).

At the beginning of the new millennia, there was a slight increase in publications and a trend towards more specific studies related to outbreaks between 1999 and 2001 in Central Asia, Russia, China, Australia as well as desert locust outbreak in 2003–2005 in West Africa. This increase is visible in a first significant accumulation of studies from 2004 with the peak in 2008. The second peak of studies in 2013/2014 is related to a special issue “Advances in Remote Sensing Applications for Locust Habitat Monitoring and Management in the Journal of Applied Remote Sensing” with a total of 14 studies. The peaks in 2018 and 2020 can be related to an open source policy and accessibility of different satellite data archives and following new approaches (e.g., soil moisture and ecological niche modelling), as well as overall increased public and research interest and available funding probably related to recent severe outbreaks.

In general, it is clear that remote sensing application studies, at least those published in the English language, were rather rare until the start of the new millennium, mostly driven by research developments in collaboration between research centers and universities with FAO and APLC for monitoring and prediction service for the desert locust and the Australian plague locust. Afterwards, the academic interest involving EO data increased in the past two decades. Nevertheless, a significant development observed in other disciplines, e.g., related to new available EO data sources (e.g., Sentinel fleet) or opening long term archives (especially Landsat) is not evident. The observed accumulation of studies is related to locust outbreaks rather than technological advances and availability of remote sensing data. However, recent analysis related to soil moisture (Escorihuela et al., 2018; Gómez et al., 2018, 2019; Piou et al., 2019) as well as ecological niche modelling (Kimathi et al., 2020; Malakhov and Zlatanov, 2020; Meynard et al., 2017) based on several data sources were the focus of investigation and showed promising results.

In terms of the investigated temporal scale, 18% of all studies were conducted only for one image representing the conditions at the time of overfly (mono-temporal). A total of 71% of studies were conducted for several images representing several states at different time steps or temporal development (multi-temporal, see also Figure 3-5). Within multi-temporal studies, we can further discriminate between studies which applied multiple mono-temporal processing steps to mirror the state at these dates (28%), and studies applying time-series analyses (43%). Studies marked as "NA" (11%) are reviews and general articles without a specific data analysis part.

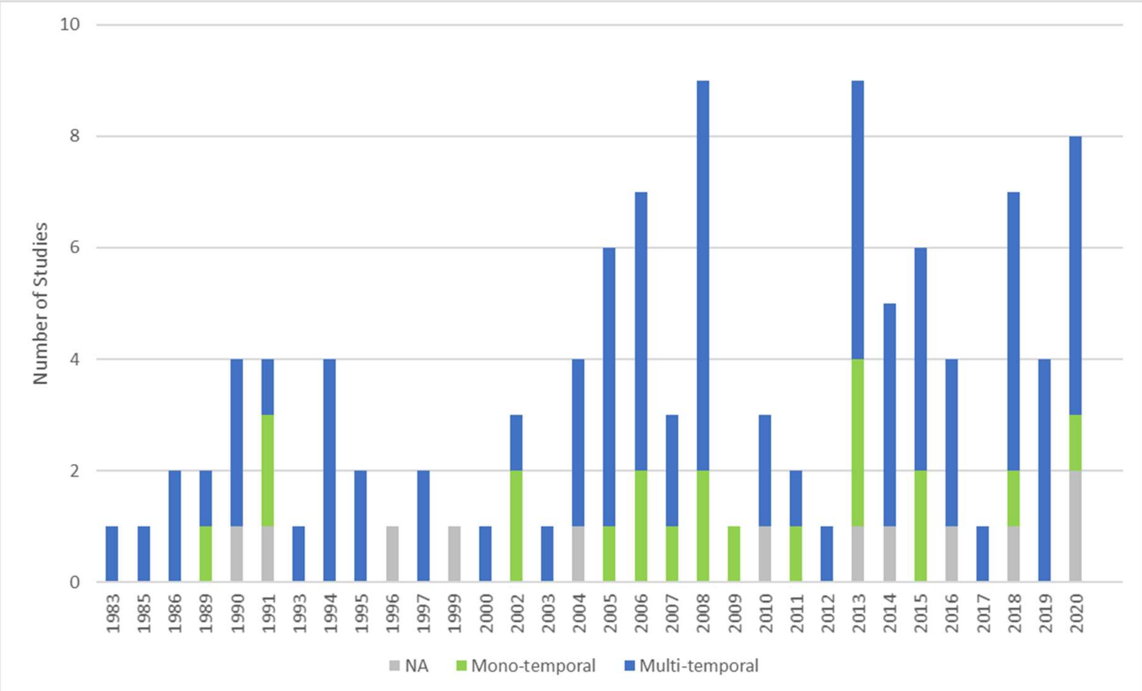

Figure 3-5. Total number of studies dealing with locust or grasshoppers applying remote sensing data (Mono-temporal = 18%, Multi-temporal = 71%, NA = 11%, see text for definitions of terms).

Figure 3-6 shows the investigated time periods. It is obvious that most multi-temporal studies focus only on few years rather than longer time periods. In total, there are only 18 studies which cover at least ten or more years (added citation in Figure 3-6).

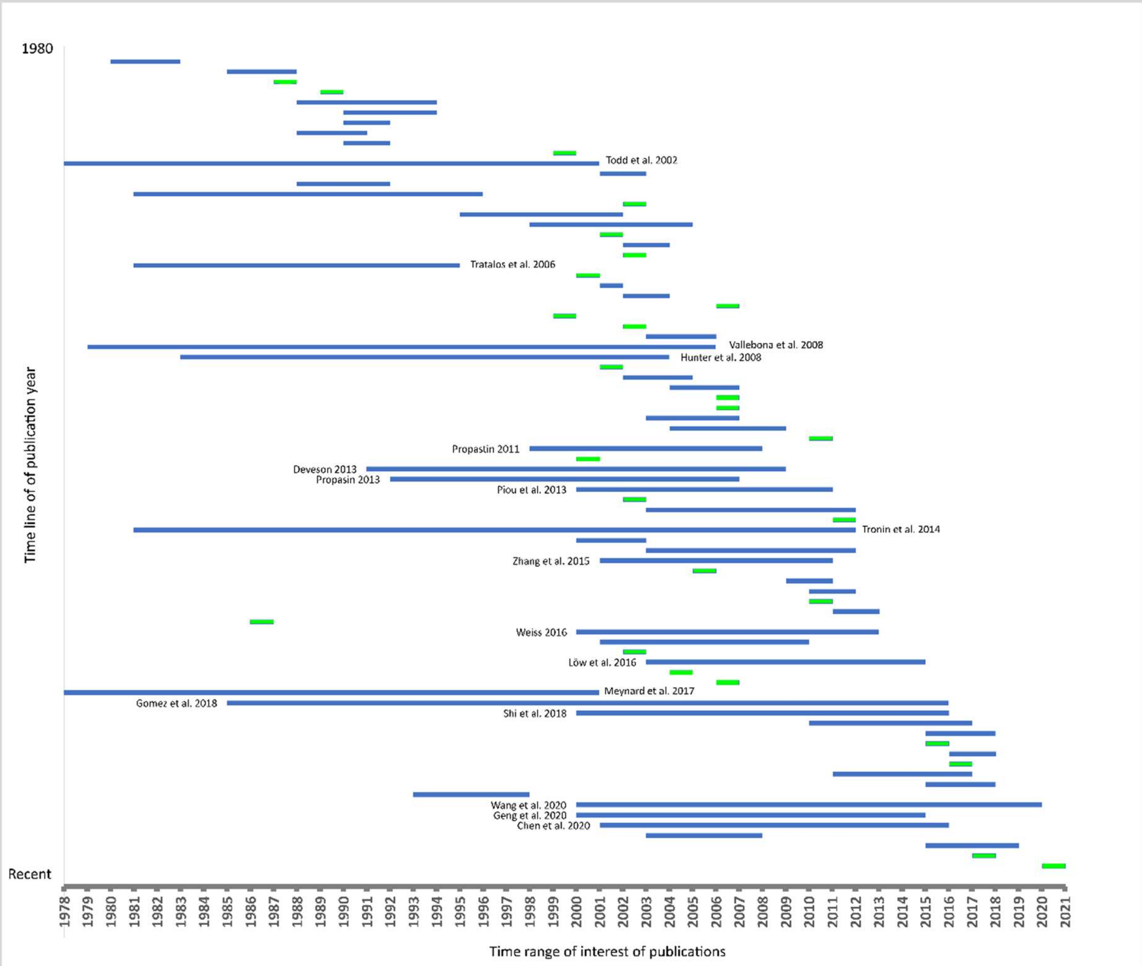

Figure 3-6. Temporal coverage of investigation within reviewed articles.
Green: mono-temporal studies, blue: multi-temporal studies; references indicate studies analyzing ten or more years

3.3.2 Publication specific aspects

3.3.2.1 Species of interest

Two species dominate the publications, i.e., the desert locust (33%) and the migratory locust (27%) (Figure 3-7). The migratory locust includes approximately ten subspecies which slightly differ biologically and morphologically, yet are characterized by similar ecological requirements (Latchininsky and Sivanpillai, 2010). Therefore, we consider this species as one overarching group. The third most investigated species is the Australian plague locust (14%).

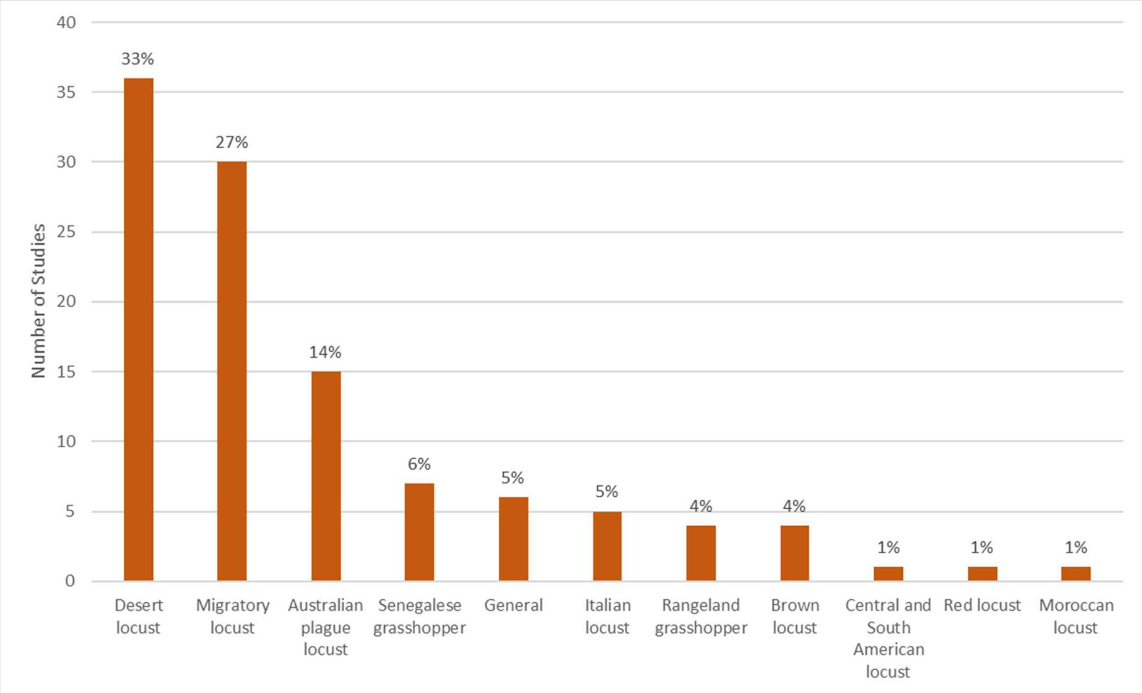

Figure 3-7. Total number of studies categorized by locust and grasshopper species.
Note: the category migratory locust includes all subspecies, e.g., the Oriental, African and Asian migratory locusts.

Few studies were found for the Senegalese grasshopper (6%), the Italian locust (5%), the brown locust (4%) and rangeland grasshoppers (e.g., *Heiroglyphus nigrorepletus, Oedaleus decorus asiaticus, Rhammatocerus schistocercoides*; 4%). Studies for other destructive species such as the Central and South American locusts (1%), the Moroccan locust (1%) and the red locust (1%) are rare. The category General (5%) does not focus on specific species but rather summarizes review papers including several species or general research which is relevant for more than one species (e.g., climate change).

3.3.2.2 Area of interest

In this section, we would like to pay attention to countries and regions of interest which were in focus of reviewed publications (Figure 3-8). Obviously, the area of interest is related to the species and its habitat distribution. Nevertheless, several species habitats cover large areas and invasion regions across several countries. For example, the countries of the Sahel region, especially Burkina Faso, Chad, Ethiopia, Eritrea, Mauritania, Mali, Niger, Nigeria, Senegal, Somalia, and Sudan are particularly susceptible to the desert locust (Kimathi et al., 2020). In general, the desert locust breeds extensively in arid and semi-arid zones extending from West Africa through the Middle East to Southwest Asia including the Arabian Peninsula, Pakistan and India. The habitat of the Italian locust spreads across Europe, Russia, Central Asia and China (Latchininsky, 2013). The different subspecies of the migratory locust such as the Asia, Oriental and African locusts are found in temperate and tropical zones of the eastern hemisphere (Latchininsky and Sivanpillai, 2010). On the contrary, the Australian plague locust, is only found in Australia.

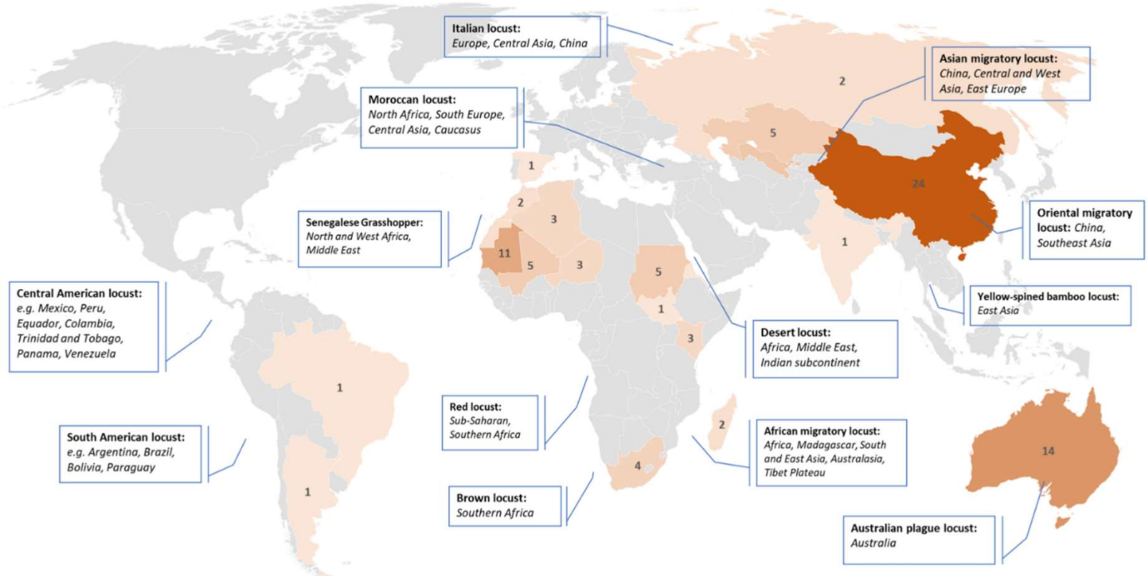

Figure 3-8. Regions of interest of reviewed studies. Comments indicate the most destructive locust species and their distribution (Cullen et al., 2017; Le Gall et al., 2019).

Most studies focused on study areas in China (26%), followed by Australia (13%), Mauritania (12%), Uzbekistan (7%) and Kazakhstan (5%). There are no studies for the Arabian Peninsula, Pakistan and only one for India, although those regions are highly vulnerable, e.g., to desert locust outbreaks. English-language publications using remote sensing for locust research or management were barely found for North and South America, South-East Asia and Europe. This may be due to minor risk of locust outbreaks (e.g., in case of Europe) or that applications use data sources apart from remote sensing, e.g., field and station measurements (e.g., in case of North America) (Belovsky and Slade, 1995; Branson, 2017, 2008).

3.3.2.3 Sensors and variables

In this section, we quantify the studies based on different sensor types, derived variables and metrics. The reviewed publications show a distinct dominance with 57% of using optical instruments only (Figure 3-9). This dominance is due to the fact that the detection of green vegetation and its density is of high importance for locust habitat monitoring as well as for damage assessment. With few exceptions the authors used data from AVHRR, MODIS, Landsat and SPOT-VGT sensors. Applications of radar sensors were found in 6% and in combination with other sensors in an additional 20% of the studies (optical/radar 10%, optical/radar/TIR 5%, radar/TIR 5%). Passive and active radar sensors are applied for soil moisture, precipitation and wind estimations. The category of sensors including thermal infrared (TIR) is related to temperature estimation which is, together with rainfall, important for monitoring as well as for hatching and outbreak prediction. In combination, there were 16% of studies using TIR (optical/radar/TIR 5%, radar/TIR 5%, TIR 3%, optical/TIR 3%). There were no studies using satellite-based hyperspectral sensors and only two studies (2%) referring to data from airborne and UAV cameras.

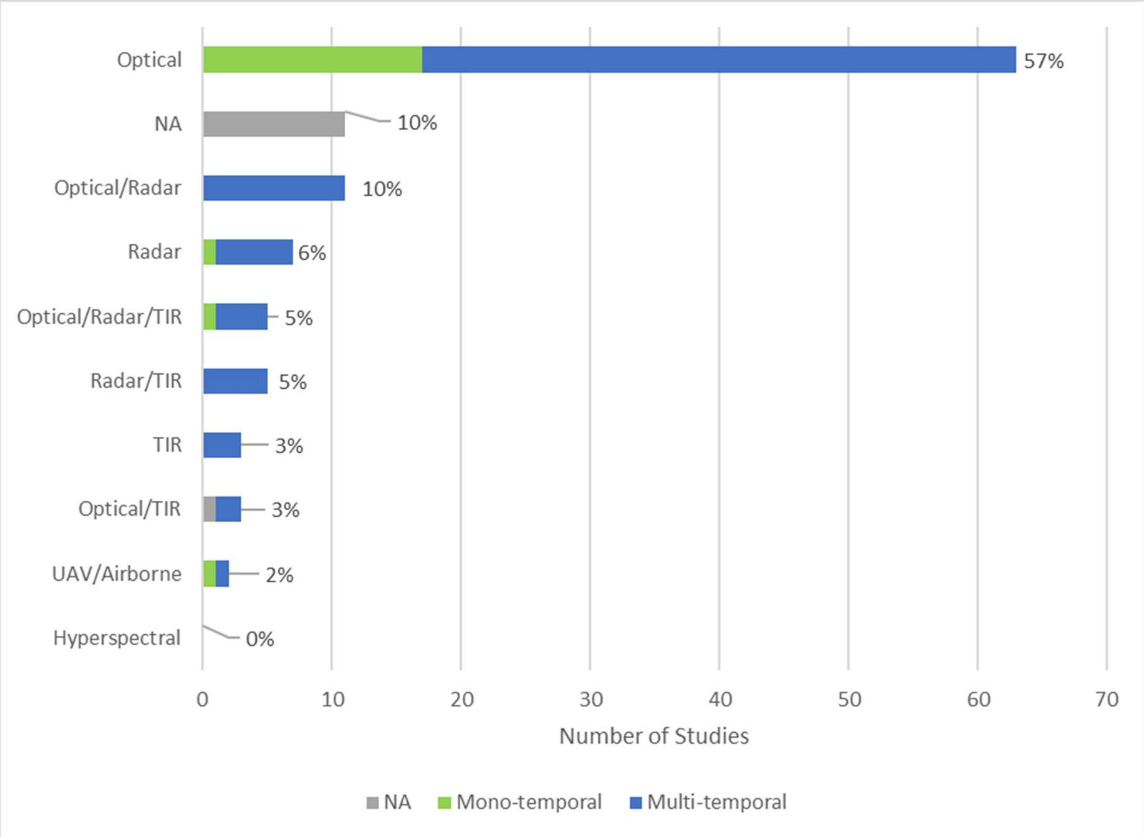

Figure 3-9. Total number of studies and remote sensing sensor types used.

Among variables, parameters and metrics, we found that vegetation indices (39%), precipitation (14%), land cover classification (13%), temperature (11%) and soil moisture (9%) are dominant (Figure 3-10). Within the vegetation indices (VI), the Normalized Difference Vegetation Index (NDVI) was applied in most cases with only few exceptions (e.g., Enhanced Vegetation Index (EVI)). Furthermore, the usage of geomorphological metrics derived either from optical or SAR data have shown great potential (Lazar et al., 2015) but its application was found only in 5% of studies. Moreover, very few studies use the Leaf Area Index (LAI) (5%) or fraction of vegetation Cover (fCover) (4%).

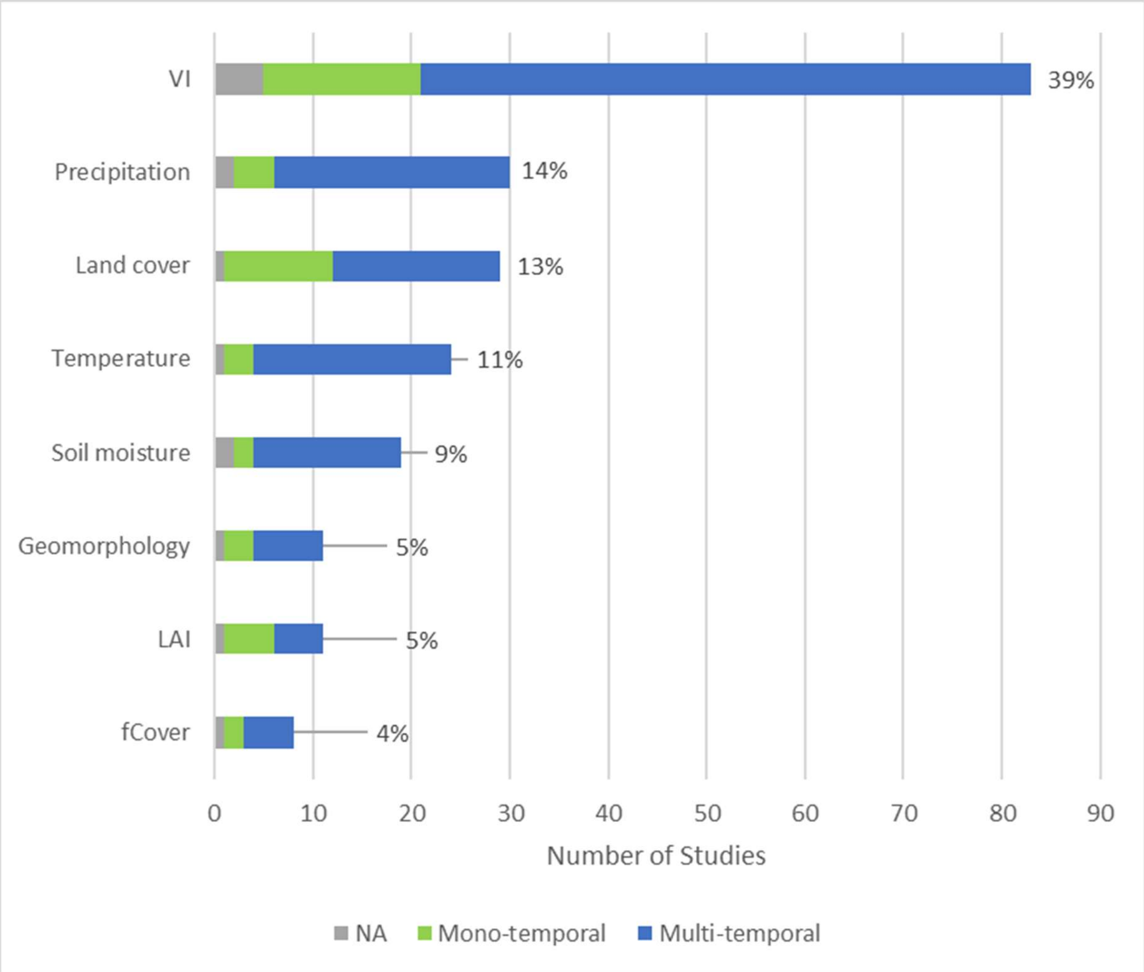

Figure 3-10. Satellite-based studies categorized into used/derived parameters/variables.

3.3.3 Thematic foci

As described in the introduction, remote sensing can add valuable information at different critical time steps of the locust life cycle (Figure 3-3). This depends on temporal as well as on spatial scale. For example, ecological niche modeling considers species-relevant variables and are mostly applied on regional to continental scales with up to 1 km spatial resolution by utilizing long-term climate data (e.g., WorldClim (Hijmans et al., 2005) or National Centers for Environmental Modeling (NCEP)/National Center for Atmospheric Research (NCAR) reanalysis data (Kanamitsu et al., 2002)) and environmental variables such as soil structure or terrain. Contrary, the damage on vegetation by instar nymphs can only be assessed with high to very-high-spatial-resolution (VHR) satellite sensors with a spatial resolution of few ten meters up to centimeters. Overall, the literature review revealed five major thematic categories (Figure 3-11):

- Habitat mapping and ecological niche modeling as static state description of potential habitat where locust might breed.

- Habitat monitoring as temporal description focusing on variable environmental parameters relevant for locust development.
- Outbreak and hatching prediction as forecast component for future.
- Damage and loss assessment as post outbreak evaluation.
- Overarching review and general research papers.

The thematic categorization of reviewed studies was performed by examining the major objectives and presented results. If the objective of a study was to map or describe habitat or ecological niche of a locust species, it is grouped into the category “habitat mapping”. The major result can be categorical habitat maps for a certain time or time period, as well as probability assessment about which areas are more prone to locust breeding. Studies which focus on monitoring or detecting changes of ecological parameters over time are grouped in “habitat monitoring”. Here, the focus is on analyses at high temporal frequency or operational monitoring of ecological parameters which affects locust life cycle and potentially contribute to early warning. Studies focusing on forecast are grouped in “outbreak and hatching prediction”. For these three categories, there are studies which might include components in line with two or even three described categories. For example, most studies grouped into “outbreak and hatching prediction” also contain monitoring aspects because it is an important tool to predict outbreaks and many forecast approaches are constructed based on statistical relationship between historical field data and relevant ecological and meteorological parameters. In these cases, we categorize based on the most important outcome. The grouping into “damage assessment” and “review and general” was more straight forward due to none intersecting objectives.

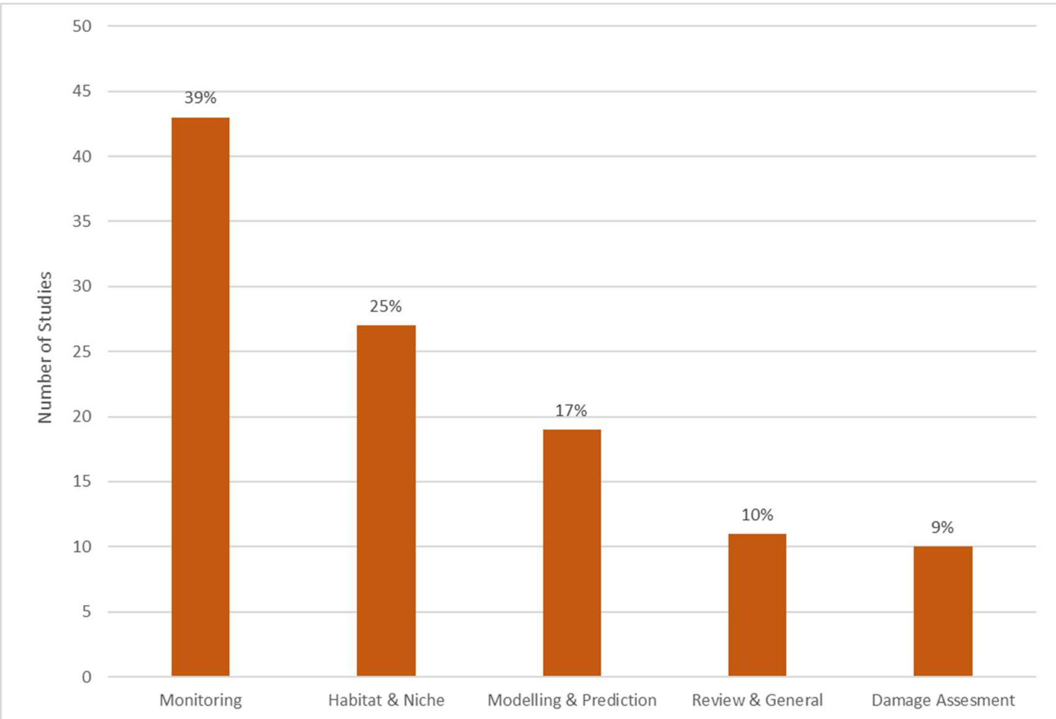

Figure 3-11. Total number of studies categorized in major research topics.

3.3.3.1 Habitat mapping studies

Identifying habitat and possible breeding sites is one of the most important tasks for implementing cost- and time effective pest control (Kimathi et al., 2020). Since the introduction of Landsat and AVHRR sensors, identifying potential locust habitats has been an essential priority for locust management services to prioritize monitoring. We identified two main approaches which have been used to map, model or classify suitable habitats of locust species, i) land cover-based habitat mapping and ii) habitat suitability assessment or modelling-based ecological niche estimation. The most important information and outcomes are summarized in following subsections for each approach.

Land cover-based habitat mapping

The first approach utilizes land cover classification methods. The outcome of land cover-based mapping are usually categorical maps of land cover or vegetation classes, which also might be converted into risk or habitat suitability classes (e.g., high, middle, low). At the beginning, researchers, e.g., McCulloch and Hunter (1983), classified locust habitats using Landsat MSS data at a 90 m spatial resolution by visual image interpretation. Based on expert knowledge about the ecology of different species and preferred vegetation types, habitats can be described by different land cover types. In this way, it is possible to indirectly assess the suitability for locust breeding. This strategy has been widely applied, especially for migratory locust species which breed in wetlands with reed vegetation (e.g., *Phragmites australis*). These habitats are highly dynamic in terms of inundation, which defines the locust population density and therefore triggers outbreaks. Sivanpillai et al. (2006) applied unsupervised classification approach using 30 m spatial resolution Landsat images in Ili river delta (Kazakhstan) to identify land cover classes which provide favorable conditions for the Asian migratory locust. A similar strategy was used in Latchininsky et al. (2007) and Sivanpillai and Latchininsky (2008) for selected Landsat images in Amudarya delta (Uzbekistan). In Sivanpillai and Latchininsky (2007) the authors identified common reed areas as potential Asian migratory locust habitats in Amudarya delta based on time-series analysis of MODIS 8-day NDVI composites (250 m spatial resolution) between April and September which represented the phenology of reed vegetation. In the same study region, Navratil and Wilps (2013) applied an object-based classification approach using one SPOT-5 image (10 m spatial resolution) to identify reed vegetation densities and categorize them into potential habitat functions such as feeding and breeding habitats. In this way, Navratil and Wilps (2013) demonstrated the potential of higher-spatial-resolution imagery as well as segmentation-based classification methodology. Later, Löw et al. (2016) analyzed MODIS EVI time series (250 m spatial resolution) between 2003 and 2014 to derive land cover for the entire Amudarya delta and relating it to migratory locust breeding sites. In this study, the authors utilize annual temporal signature to achieve high classification accuracy for each year. The classification results are finally used to derive potential risk categories and in this way support locust management.

Additionally, research efforts on habitat mapping have been conducted for the migratory locust in several study sites in China. Q. Liu et al. (2006) applied land cover classification-based approach to derive potential habitats in Yellow River delta based on one Landsat TM (Thematic Mapper) image. Li et al. (2011) used 14 HJ-1 CCD images (30 m spatial resolution) to derive NDVI time series to produce a land cover classification map and convert it to potential habitats of Asian migratory locusts in Hebei Province. Zheng et al. (2018) applied decision tree-based classification for six Landsat Operational Land Imager (OLI) images in the Dongying region to derive Oriental migratory locust habitat in 2015. Shi et al. (2018) analyzed time series of MODIS and Landsat data between 2000 and 2016 to estimate annual changes in Oriental migratory locust habitat. Recently, Zhao et al. (2020) identified land cover and land use changes in Oriental migratory locust habitats for entire China. They classified multi-annual Landsat TM, Enhanced Thematic Mapper (ETM) composites generated from data between 1993 and 1997, 2003 and 2007 and 2015 and 2018 to compare the habitat status in the years 1995, 2005 and 2017 concluding that Oriental migratory locust habitats decreased due to the change in land use. Geng et al. (2020) introduced a Patch-based Analytic Hierarchy Process (PB-AHP) and Habitat Suitability Index (HSI) model based on MODIS and Landsat time series to analyzing Oriental migratory locust habitat factors in Tianjin province that affect locust oviposition and growth. The habitat factors included vegetation coverage, land cover classification, soil moisture, soil salinity and land surface temperature. The PB-AHP model was used to derive weight coefficients for each habitat factor and the degree of patch scale suitability by quantitative analysis of landscape structure and in this way map locust habitat at different suitability levels.

On the contrary to reed vegetation for the migratory locust, the detection of plant species which are favored by other locust species is more challenging due to the spectral characteristics of most optical sensors. Therefore, studies for other locust species rather focus on the general state of vegetation as a proxy for favorable breeding or invasion areas. For example, Bryceson (1989) utilized Landsat MSS data to determine the location of Australian plague locust eggbeds based on vegetation greenness as areas favorable for invasion and land cover type as areas favorable for oviposition. She concluded, however, that using only NDVI information without land cover information (e.g., woods, forest versus grassland and shrubland) remains problematic. In this context, Bryceson (1989) shows a high correlation between low NDVI values (−0.13 to 0.04 range) and localized nymph bands for certain land cover types (grasses and forbs and natural pasture). De Miranda et al. (1994) used Landsat images to map the static state, and AVHRR-based NDVI time series to map the dynamic development of the biotopes of one grasshopper species (*Hammatocerus schistocercoides*) in Mato Grosso, Brazil. Dreiser (1994) and Voss and Dreiser (1997) produced detailed habitat maps for selected pilot regions within the recession area of the desert locust in Sudan, Mali, Mauritania and Niger using Landsat data, field observations and expert knowledge. Another approach was introduced by Lazar et al. (2015), who integrated 43 years of field data in combination with selected Landsat images to classify main breeding sites of the desert locust during solitary phase. Their approach focused on identifying geomorphological structures such as wadis. The results for the pilot region in southern Algerian Sahara show that wadies contained 81% of observed laid egg pods according to the field data archive. Lazar et al. (2015) suggested ignoring the vegetation dynamics and focusing on correlations between breeding areas of solitary locusts and specific geomorphological features such as wadis. On the other hand, the study states also that 19% of laid eggs within the test region were outside of such areas. Therefore, such approach should be applied in combination with vegetation dynamics to account for all suitable areas.

A unique human-locust species inter-connection example can be found by examining the Italian locust. The Italian locust prefers sagebrush (*Artemisia spp.*) which also grows on fallow and abandoned fields, overgrazed pastures, as well as along roads and other man made structure (Kambulin, 2018; Latchininsky, 2013). However, when crop fields are plowed, the egg pods of the Italian locust are destroyed mechanically. Therefore, land management practice and abandoned fields as well as artificial landscapes directly influence areas favorable for Italian locust breeding. In this context, Sivanpillai et al. (2009) presented a case study for mapping Italian locust habitats in Northern Kazakhstan. The authors used an Advanced Wide Field Sensor (AWIFS) scene at spatial resolution of 56 m to discriminate active and abandoned fields to identify potential breeding areas. Furthermore, Liao et al. (2013) investigated three critical development stages for the Italian locust relevant to locust density—breeding stage, incubation stage and development stage—to assess a risk index in Xinjiang, China. The authors identified soil texture, vegetation species and geographic elevation as relatively temporal static geophysical properties and combined them with dynamic soil moisture, vegetation coverage, air temperature and rainfall variables. Finally, suitability index was derived for each development stage and combined to a locust plague risk index (LRI).

Modelling-based habitat suitability mapping

Another approach to identify habitats is based on spatial distribution models (SDM) or ecological niche models (ENM) by combining locust presence locations (derived from ground surveys) and different sets of environmental variables. ENM are usually based on machine learning algorithms to correlate a set of environmental conditions to species presence and absence records and thus predict its suitable habitats (Kimathi et al., 2020). The output of such models reflects habitat suitability by fitting a probability distribution for selected species over a specific region of interest.

Aragón et al. (2013) estimated climatic favorable areas for different locust species distribution and outbreaks in Spain, utilizing bioclimatic variables derived from WorldClim data and historical outbreak records. The authors tested several SDMs and summarized that temperature annual range, precipitation of the coldest annual quarter and estimated Acrididae richness had the highest influence modelling historical outbreak results. Furthermore, the authors used the Global Land Cover 2000 product (based on SPOT-4 imagery) to derive land use and assess the risk in economic important regions. Zhang et al. (2015) selected key habitat factors by intersecting field data with different environmental variables such as soil properties, MODIS NDVI, geomorphological parameters derived from digital elevation model (DEM) to finally map the potential occurrence of grasshoppers (*Oedaleus decorus asiaticus*) in the Inner Mongolia steppe. Relevant climate variables influencing oviposition, overwintering and incubation were considered within a fuzzy evaluation model (multi-objective linear weighted function).

Malakhov et al. (2018) pointed out that their model is able to identify areas where, at a certain time, a successful development of locust eggs is most probable, rather than to predict the actual oviposition areas. For locust management, however, the question “which areas provide favorable conditions for egg survival” is even more critical. Based on their analysis for the Asian migratory locust in Ili river delta (Kazakhstan), the ambient air temperature; the temperature of the soil during the cold season of the year, soil moisture, and the presence of reed vegetation which was classified from MODIS data were most important variables to map optimal oviposition areas. Similarly, Malakhov and Zlatanov (2020) developed an ENM for the Moroccan locust combining a total of 74 variables (including satellite-based NDVI and Soil Water Index) and this way identifying favorable condition for egg pods survival. The output reveals that 58% of key variables describe winter and spring conditions, which relates to most vulnerable life stage of this species (embryogenesis and nymph development).

Recently, Kimathi et al. (2020) used maximum entropy model and desert locust field data to derive potential breeding areas across affected countries in East Africa. They used long-term temperature and precipitation (based on 1970–2000 data from WorldClim2) to calculate the long-term mean for December, January, February and March as well as an average soil moisture and soil sand content (at a depth of 5–15 cm). Furthermore, they included a 10-day composite vegetation greening onset product which is based on SPOT and MODIS data to assess vegetation development within modelled breeding areas. However, the authors stated that additional detailed assessment of temporal variation in vegetation prevalence and vegetation type could improve the accuracy of the model (Kimathi et al., 2020).

3.3.3.2 Habitat monitoring studies

In the following, we summarize studies which focused on the temporal monitoring of environmental conditions, which determine the phase change as well as the timing of hatching. In this way, those studies focus on information about temporal dynamics rather than a static habitat status or potential species distribution as described in the previous section. Another main difference to previous section is that following studies potentially contribute to operative service or enable immediate decisions as part of early warning system (e.g., sending field teams for on ground monitoring or control measurements). The majority of habitat monitoring studies were focusing on precipitation and soil moisture monitoring as well as assessing vegetation change.

Early research conducted by Cherlet et al. (1991), Hielkema et al. (1990, 1986), Hielkema, Hielkema and Snijders (1994), Tucker et al. (1985) discussed different approaches on how Meteosat or AVHRR data can be utilized for monitoring desert locust habitats especially during recession periods as well as for the Senegalese grasshopper (Tappan et al., 1991, 1990; Tappan and Moore, 1989). The geostationary Meteosat satellites provides data to monitor weather system over large areas at very high frequency. The identification of “cold” rain-bearing clouds, based on threshold approach in thermal infrared (TIR) channel, enables the location of areas where sufficient rainfalls and soil moisture can lead to egg hatching (Cherlet et al., 1991; Milford and Dugdale, 1990). In Hielkema et al. (1986) the potential breeding activity factor (PBAF) was introduced as a function of amount of pixels for four different NDVI ranges. Based on these research, remote sensing applications were implemented into FAO monitoring systems (Africa Real Time Environmental Monitoring Information System (ARTEMIS)) and build the base for instructions and guidance for national and regional desert locust management offices in affected countries. In this context, the estimation of precipitation has been the main aspect for locust and grasshopper monitoring. Dinku et al. (2010) evaluated and compared seven different satellite-based rainfall detection products, which are based on thermal infrared (TIR) observations and long microwave (LM) rainfall estimation. The authors concluded, that in arid and semi-arid areas, a significant overestimation of rainfall occurrences turned out as the main weakness. Nowadays, 24-hours, 10 days and monthly rainfall cumulative products which are generated by Climate Prediction Center MORPHing (CMORPH) algorithm are used for operative monitoring (WMO and FAO, 2016).

Recent research to monitor (i) vegetation, (ii) soil moisture, and (iii) studies which investigate combination of several ecological import variables are summarized in following three subsections.

Monitoring vegetation change

In the last 15 years, there was increased development in monitoring vegetation. Major focus was placed on temporal scale and relation of vegetation indices variability to locust development.

Ceccato (2005) combined 10-day NDVI composites at 1 km spatial resolution from SPOT-VGT with spectral bands to analyze favorable conditions of the desert locust for reproduction and development. They discussed the issues of significant commission and omission errors critically and recommended to add selected spectral bands (e.g., RED, NIR, SWIR) to reduce the commission error or to add MODIS data to detect sparse vegetation, which was omitted due to coarser spatial resolution of SPOT-VGT NDVI data. Furthermore, Ceccato et al. (2006) presented useful applications of decadal rainfall satellite products and MODIS 16-day NDVI data to monitor the climate variability and its integration into early warning systems for desert locust management.

Tratalos and Cheke (2006) found that in arid regions, coarse-scale NDVI rather correlates with precipitation than with locust population. Chen and Li (2008) analyzed LAI derived from Landsat images and presence of the Oriental migratory locust and stated a significant linear relationship between LAI and the occurrence of locust density.

In Pekel et al. (2011), the authors addressed the previously stated issues with high omission and commission errors in arid regions and developed a more reliable multi-temporal approach based on MODIS data and a colorimetric transformation to identify vegetated areas in near real time. The color transformation projects the red, green, blue (RGB) bands to hue, saturation and value (HSV) where hue appears as a qualitative spectral index, and its temporal variations can be interpreted as land cover change. Cressman (2013) reported that the technology for green vegetation estimation is useful and accurate in terms of operation and usability in early warning system for desert locust monitoring. There, the operational use of NDVI and EVI 16-day composites from MODIS data seems to provide sufficient information to detect changes in ecological conditions, specifically greening and drying vegetation. Cressman (2013) also referred to a color space-transformed HSV product developed by Pekel et al. (2011), which is able to mirror the development of vegetation; moreover, he pointed out that 11 periods of 10-day composites correspond roughly to the length of one desert locust generation. The Pekel et al. (2011) approach is also used operationally for FAO early warning systems and daily locust control activities. Waldner et al. (2015) assessed the accuracy of the dynamic greenness maps and revealed a high accuracy in summer breeding areas of the desert locust (F-score of 0.64 to 0.87); however, they are less accurate in winter breeding areas (F-score of 0.28 to 0.40). Furthermore, the accuracy of the product depends on landscape fragmentation ($R2 = 0.9$). Therefore, the

MODIS spatial resolution is still too coarse to resolve complex landscape patterns, which were responsible for 60% of the error (Waldner et al., 2015). In this context, Waldner et al. (2015) further compared PROBA-V 100 m resolution data and found that the higher spatial resolution lowers the resolution bias in fragmented areas by 20% and increases the quality of the vegetation classification. Finally, Renier et al. (2015) tested the hypothesis that a reliable discrimination of the onset of vegetation senescence can be achieved by jointly implementing temporal NDVI trajectories and the Normalized Difference Tillage Index (NDTI), which is sensitive to both green and dry vegetation. The authors used MODIS SWIR band, which has shown to be effective to monitor dry vegetation. Based on these two indices, the authors calculated eleven different metrics, which should represent three phenological classes "growth", "density reduction" and "drying". In Mauritania, MODIS 10-day composites were applied to identify onset of drying as an indicator that a habitat becomes less attractive to the desert locust. The authors further state that higher spatial resolution may play a crucial role to improve vegetation classification in arid and fragmented areas.

Additionally, Deveson (2013) reported that for the APLC model, using the relative NDVI (r-NDVI) showed significant positive relationship between one-month change in r-NDVI and the presence of nymphs and nymph density for the Australian plague locust. Additionally, Wang (2014) quantitatively assessed that greening of Australian plague locust habitat is related to locust appearance and population density.

Monitoring soil moisture

Soil moisture plays a crucial role for locust development. Early studies on soil moisture showed its potential, but also the restrictions of applying satellite-based radar data to operational services due to low spatial and temporal resolution (Crooks and Archer, 2002). Liu et al. (2008) presented an approach exploiting MODIS-based soil moisture and its relationship with Oriental migratory locust plagues. They found that the soil moisture content was lower during a severe outbreak period. Moreover, they concluded that the severe outbreak was clearly impacted by reduced soil moisture during locust oviposition and incubation periods.

Escorihuela et al. (2018) presented a first attempt to implement soil moisture products within operative desert locust management tools. Different user requirements and soil moisture algorithms were assessed to produce a soil moisture product at 1 km spatial resolution. Furthermore, they present an innovative approach to derive soil moisture at 100 m spatial resolution by synergizing Sentinel-1 with Soil Moisture and Ocean Salinity (SMOS) data. Gómez et al. (2018) investigated the relation between desert locust presence during the solitarious phase and soil moisture conditions based on European Space Agency (ESA) Climate Change Initiative (CCI) soil moisture product (spatial resolution 0.25°). The authors analyzed the relation between the presence of the desert locust and soil moisture change for different time intervals before the date of sighting. In conclusion, the shorter time intervals of six days performed the best result and indicating that most important time interval was between 95 and 72 days before desert locust nymph presence was detected in the field.

Monitoring of Several Variables

In this subsection, we summarize studies which presented monitoring strategies combining several variables of importance. Han et al. (2006) presented a remote sensing-based model including LST, soil moisture, NDVI, fCover, and LAI for monitoring the East Asian migratory locust based on three different locust life cycle stages. Similarly, Gornyy et al. (2006) stated that satellite monitoring enables the monitoring of ecosystem state as well as locust population. They investigated several land surface characteristics such as heat flow, evaporation rate and NDVI from AVHRR and MODIS data in relation with Italian locust density based on the fact that daily averaged evaporation rate of surface depends on the moisture supply on ground and on the possibility of vegetation to evaporate water. For the test region of southern part of West Siberia, the authors concluded that with higher soil moisture the locust population was less dense.

Another alternative monitoring approach was presented by Propastin (2013) combining radar altimetry measurements with NDVI data (AVHRR and SPOT-VGT) to monitor the habitat of the migratory locust in Ili river, Kazakhstan. In these studies, the author found that the water level of lakes and rivers, which can be derived via radar altimetry, directly affect the distribution of common reed vegetation which influences potential habitats as well as areas for infestation.

Li et al. (2014) presented a design for GIS-based monitoring and control for the migratory locust in China which also includes processing of NDVI, soil moisture and emissivity time series from MODIS data. Latchininsky et al. (2016) presented different remote sensing-based applications to monitor the red locust in Madagascar using SPOT-4 and DEM data, the migratory locust in Amudarya river delta using Landsat data and the desert locust in Mauritania using MODIS data.

Gómez et al. (2019) applied different machine learning approaches to create a species distribution model by integrating six environmental variables from two sensors: MODIS-based NDVI and land surface temperature (LST) as well as Soil Moisture Active Passive (SMAP)-based soil moisture root zone, surface soil moisture, LAI and surface temperature data. Based on these variables in combination with locust presence field data, the authors modelled breeding suitability for the solitary desert locust. Within their analyses the authors identified surface temperature retrieved from SMAP as most important parameter. On the contrary, MODIS LST was not as relevant. Gómez et al. (2019) point out that for monitoring the time of temperature retrieval is crucial in semi-arid and arid regions with high day-night temperature range and explain the different performance for same physical variable from two different sources. In conclusion, the most relevant variables were surface temperature, NDVI, soil moisture at root zone under different time scenarios. By including all six environmental variables, the authors obtained high predictive performance (Kappa = 0.901; ROC = 0.986).

Chen et al. (2020) used multiple satellite-based datasets (NDVI, LAI, soil moisture, rain fall between 2005 and 2020 and distribution to simulate potential geographic distribution of the desert locust for Africa, Asia and Europe for different months. They coclosed that LST (27.02%) and LAI (25.63%) were the main contributors to explain the achieved distribution results. Surprisingly, soil moisture was the weakest explanatory variable (2.7%). Recently, Wang et al. (2020) assessed whether China is also prone to desert locust invasion during the 2020 outbreak in East Africa, India and Pakistan. The authors, identified potential desert locust habitats in China by applying simple long-term thresholds for precipitation and temperature. Afterwards, they modelled windborne movements of the desert locust to those identified potential habitats based on historical wind characteristics at different altitudes, concluding that significant invasion of potential habitats in China is very unlikely.

3.3.3.3 Outbreak and hatching prediction studies

In this section, we focus on studies which specifically target prediction of locust outbreaks or the beginning of hatching. Compared to monitoring studies from previous sections, the focus is on the future, although historical data, past measurements and monitoring are essential part of those studies. According to Rosenberg (1999), the focus of locust forecast has shifted from population dynamic-based prediction of swarm development and movement towards identification of rainfall and vegetation change that initiate the growth of existing locust populations and therefore may indicate beginning upsurges and plagues. Rosenberg (1999) reported that for locust forecast there are three main scales to be considered: the long-term forecast with up to 12 months is based on climate, historical data, derived anomalies and pest frequencies. One example is the FAO SWARMS (Schistocerca WArning Management System) which contains historical data back to 1930 and enables large-scale analysis for the entire desert locust distribution areas. The medium- to short-term forecast with 1–2 months and 1–2 days are handled at a national scale, e.g., operating RAMSES (Reconnaissance And Management System for the Environment of Schistocerca) where different months can be compared with previous months and same months of other years (Rosenberg, 1999).

First of all, Healey et al. (1996) introduced the requirements for a GIS to support desert locust operational forecasting and monitoring. The authors underlined the importance and further implementation of weather and habitat data derived from remote sensing sources. Burt et al. (1997, 1995) proposed the usage of Meteosat IR data to estimate rainfall from cloud temperature and support forecasting early season outbreak of the Senegalese grasshopper in West Africa. The authors conclude that this approach enables to spot areas of sufficient wetting, where the Senegalese grasshopper might hatch after 2–3 weeks.

Todd et al. (2002) analyzed the impact of climate variability on brown locust outbreaks in southern Africa by implementing historical climate data. Brown locust outbreaks were associated with increased rainfall in December which is also related to La Nina events. Their results suggested that there is considerable scope for future development of models for the seasonal prediction of brown locust activity in which high-frequency variability is related to climatic indices (Todd et al., 2002). Ma and Dai (2005) utilized MODIS data including NDVI, LAI, soil moisture, LST and fCover within a Bayesian prediction network to forecast the evolution of these variables, which are responsible for Asian migratory locust outbreaks. Ceccato et al. (2007) analyzed the desert locust outbreak in 2003/2004 in West Africa and accompanying circumstances which favored the outbreak. They used rainfall predictions to forecast the risk of future desert locust outbreaks. Within their study, Ceccato et al. (2007) also reviewed the desert locust early warning system, and assessed the feasibility of new climate prediction methods to support forecasting desert locust life cycle development and locust movements. Here, the FAO SWARMS operates on a daily basis using RAMSES ground information, meteorological data and remotely sensed images (NDVI from SPOT-VGT at 1 km and MODIS at 250 m spatial resolution for monitoring vegetation development) to conduct short- and medium-term forecasts indicating potential locust migrations and breeding areas. Additionally, the International Research Institute for Climate and Society (IRI) is forecasting environmental conditions for desert locust development to accurately predict preferable conditions, and in this way increase the response time for further reaction and preparation of controlling steps if required. IRI specifically focuses on long-term prediction of rainfall, because it is critical to the locust outbreak forecast. In this context, Ceccato et al. (2007) also discussed that seasonal prediction of rainfall in North Africa is less clear due to the midlatitude storms, whose frequency and intensity are unpredictable. Long-term rainfall forecast results can be improved where oceanic conditions in the atmospheric circulation evolve relatively slowly.

Vallebona et al. (2008) analyzed connections between large-scale climatic patterns and desert locust upsurges in West Africa between 1979 and 2005 using NCEP-DOE Reanalysis 2 data at monthly resolution and 2.5° grid cells as well as desert locust population dynamics from multiple sources.

Piou et al. (2013) presented a forecast method coupling historical field survey and NDVI data (MOD13Q1 NDVI 16-day 250 m product) to analyze the influence of vegetation change within desert locust habitat in Mauritania. They smoothed the NDVI time series with Savitzky-Golay filter and derived in total 27 spatial and temporal vegetation metrics before the date of observation. NDVI values were extracted for different time intervals before field survey timing (16 days, 32 days, 48 days). The authors used logistic regression model to assess the relationship between all metrics and ground control points. Their analysis showed that temporal changes of NDVI between 32 and 48 days before a locust occurrence, provided the best prediction results. The results indicated that metrics describing vegetation change allow prediction of locust presence during remission periods. At local scale, Piou et al. (2013) identified a non-linear relationship between mean vegetation quantity and presence of the desert locust, even if they did not consider geomorphologic variables, which plays important role for breeding sites of the desert locust (e.g., wadis and areas with water accumulation). However, the maximum NDVI followed the topographical structures. Therefore, Piou et al. (2013) argued that locust population development follows vegetation development; they also state that rainfall, the time lag between the observed vegetation changes and locust presence is critical for locust prediction. The authors summarized, that tools transforming NDVI maps to predictive presence/absence maps are required to improve locust management.

Cressman (2013) presented an overview for the role of remote sensing in FAO early warning systems for the desert locust which are conducted in collaboration with national locust management organizations. The DLIS constantly monitors weather, habitat conditions and desert locust population in recession areas. This holistic observation is further used to assess the current situation and to predict the locust developments. Nevertheless, Cressman (2013) stated that the spatial resolution and sensor characteristics of implemented MODIS data limit the detection of sparse vegetation that is critical for locust survival and reproduction.

For the Italian locust, Tronin et al. (2014) introduced the locust hazard index (LHI), which is a linear combination between NDVI, an aridity index, and the number of sunspots. The authors also investigated LST and precipitation and concluded that there was a significant relation between droughts in 1986–1991 and 1996–2000 and Italian locust outbreaks in

1988–1991 and 1999–2001 in the Siberian study region. For both periods the LHI showed good results and therefore could be potentially used as a prediction tool. Following this conclusion, Tronin et al. (2014) suggested a threshold for the LHI to assess Italian locust outbreaks in the Siberian study region. In contrast, LHI did not provide reliable results for the European study region. The prediction reliability for both regions was assessed based on false alarms and missed outbreaks. They concluded that LHI did not perform well for European study region due to the larger size and its diverse landscapes, biomes and meteorological conditions.

For eastern Australia, Veran et al. (2015) used MODIS data to estimate different proportions of woody and herbaceous vegetation, together with temperature and precipitation to model the spatial-temporal dynamics of the Australian plague locust. The spatial variability of outbreaks was best explained by rainfall and land cover predictors across eastern Australia. Furthermore, the authors summarized that their results show an improvement for locust outbreak forecast by implementing key environmental factors and migration in hierarchical spatial models. Zheng et al. (2015) introduced a GIS-based prediction model including monthly average temperature, monthly relative humidity, elevation, slope, NDVI (from SPOT-VGT) and soil PH data for Xinjiang province, China. They reached satisfying forecast results with a multi-criteria analysis (MCA). Weiss (2016) conducted detailed research on relationship between Australian plague locust adult abundance and greenness derived from MODIS-based vegetation indices composites (8-day GPP, 8-day FPAR, 16-day NDVI) at 1 km spatial resolution. Applying a Bayesian hierarchical analysis, he concluded that all vegetation indices were weak predictors for adult locusts and investigated time period between 2000 and 2009 and therefore were no link between pests and vegetative conditions. In Mangeon et al. (2020), the authors present statistical model approaches using Generalized Linear Models (GLM) and Generalized Additive Models (GAM) to quantify relative strength of different variables influencing Australian plague locust population and estimate locust abundance. Their results indicate divergent relationship for NDVI with adults and nymphs. The prediction performance was best for nymphs (R^2=0.461) underlining the local environment dependence of this life stage (Mangeon et al., 2020).

Apart from using rainfall and vegetation as variables for locust forecast, soil moisture is another critical variable to be considered. For brown locust life cycle modelling, Crooks and Cheke (2014) assessed the usability of C-band SAR data (from RadarSat and ERS-2) for soil moisture retrieval as an alternative to rainfall estimation. They summarized that future application of SAR images will depend on the feasibility to acquire data on a spatial and temporal scale that is useful for forecasters.

Meynard et al. (2017) analyzed ecological niche differences between South and North desert locust subspecies during the solitarious phase and possible future shifts in geographical distribution based on climate change scenarios. Using a set of SDMs and climate variables, the authors concluded strong niche conservatism between both subspecies. Piou et al. (2019) investigated temporal development for NDVI, soil moisture, rainfall and land surface temperature around survey points of desert locust presence in recession areas. The authors applied statistical analysis for all variables separately to assess their individual potential to explain and forecast desert locust presence. In this context, NDVI was the best explanatory variable (Area under the receiver operating characteristic curve (AUC) = 0.7264), followed by soil moisture (AUC = 0.6280), LST (AUC = 0.6201) and rainfall (AUC = 0.5797). In terms of vegetation response, the period of 0–48 days was found to be most important after NDVI value reaches 0.14 or higher. Additionally, very low NDVI values (below 0,10) between 160 and 80 days before locust presence, was also important. Furthermore, the analyses revealed higher chances to find locust nymphs 70 days after soil moisture increased over a period of 20 days (above 0.09 cm3/cm3) and followed by consecutive decrease. Hereafter, the random-forest forecast model combining soil moisture data with NDVI showed promising results with high AUC value of 0.761 and out of the box error of 23.7%. The model validation for years between 2010 and 2016 reached AUC between 0.583 and 0.709 and error between 27.6% and 39.7%.

3.3.3.4 Damage and loss assessment studies

Stressed or damaged vegetation is characterized by a difference in reflectance compared to healthy vegetation. Due to loss of chlorophyll stressed vegetation can be detected in red edge spectrum. Extreme loss of green vegetation is visible in VI (change in spectral reflectance) as well as in high-resolution SAR (change in canopy cover and structure). Studies focusing on damage assessment were conducted mainly for migratory locusts in China. These studies assessed vegetation patterns before and after a specific outbreak and thus identified affected areas. The information on whether there is a causal relation between damaged vegetation and locust swarms was mostly based on a priori knowledge and assumptions of the authors that no other factors contributed to the damage. All following reviewed vegetation damage studies can be considered as case studies at local scale and therefore with limited spatial coverage. For the East Asian migratory plague locust, Ma et al. (2005, 2002) performed a calibration and verification study for Landsat data to detect damage in reed habitats. In their experimental study, Ma et al. (2002) investigated whether field measurements of biomass and LAI and Landsat-based NDVI/ARVI (Atmospherically Resistant Vegetation Index) are related during locust presence ($R2 = 0.6474$). Ji et al. (2004) used MODIS NDVI time series to assess damage due to an Oriental migratory locust outbreak in Hebei Province, China. Zha et al. (2005) analyzed MODIS-based multi-spectral indices using temporal filtering and concluded that NDVI was the best index to assess damages caused by locust outbreaks. Liu et al. (2006) and Tian et al. (2008) calculated Landsat-based NDVI difference maps to assess the differences before and after outbreak event. With the focus on vegetation loss, Zha et al. (2008) introduced the Locust Density Index (LDI) which considers the initial state of vegetation as well as the destroyed vegetation after infestation. Singh et al. (2007) conducted measurements with a ground-based X-band Radar to assess the damage by *Heiroglyphus nigrorepletus* on sorghum. Furthermore, Song et al. (2020) estimated reed loss caused by the migratory locust using UAV-based data.

Weiss (2016) also investigated the capacity of MODIS 1 km temporal composite products to map vegetation damage caused by nymph bands of the Australian plague locust. The extensive statistical analyzes between prior, during and post presence of bands showed no significant relation to area extent or intensity of damaged vegetation. In conclusion, Weiss (2016) stated that coarse spatial and spectral resolution as well as temporal compositing methodology of used products were the main reason why vegetation damage caused by nymph bands feeding was not detected.

Additional to satellite-based studies it is interesting to note that Hunter et al. (2008) analyzed Australian plague locust bands which were observed from an airplane. There, the accumulation of locust nymphs as well as damaged vegetation is clearly visible in RGB images. VHR satellite data (e.g., WorldView-3, GeoEye, SuperView) as well as data from UAV and very-high-spatial-resolution sensors should be capable of spatially resolving such accumulation of locusts and damaged vegetation.

3.3.3.5 Review and general studies

In our literature search, we found six review and four general discussion publications dealing with locust pests and remote sensing applications. Cracknell (1991) discussed general capacities of remote sensing detecting habitat changes and applicability for locust management. Hunter (2004) presented APLC activities and demonstrated that Australian plague locust bands can be spotted using airborne imagery with spatial resolutions similar to today's VHR satellites. Maiga et al. (2008) review paper focused specifically on the ecology and management of the Senegalese grasshopper. The authors summarized also the potential of remote sensing and encouraging results for the Senegalese grasshopper from early studies on AVHRR NDVI and Meteosat IR data which demonstrated that suitable breeding areas can be identified with simple thresholding methods.

Latchininsky and Sivanpillai (2010) presented an overview of existing EO sensors, their spatial and temporal scales as well the potential of GIS technologies for locust monitoring and risk assessment to promote these technologies for further usage. Further, Latchininsky (2013) gave a comprehensive state-of-art review showing that in 2013 most operative applications were conducted by FAO and APLC, focusing on vegetation and meteorological parameters. Additionally, Latchininsky (2013) provided details for other destructive locust species, their ecology and EO applications for their monitoring.

Huang (2016) provided a review on EO application for locust and grasshopper plagues specifically in China focusing more on ongoing research in monitoring as well as risk and loss assessment. For risk assessment, Huang (2016) summarized that habitat mapping by multi-spectral land cover classification (Landsat, ASTER, HJ-1 CCD) was dominant. For monitoring, studies focused mostly on vegetation (MODIS time series), soil moisture and land surface temperature with high temporal resolution due to rapid changes of these critical variables.

The review paper of Zhang et al. (2019) covered control measurements and locust ecology but also paid attention to EO as an important tool in modern locust management. This review provides a comprehensive overview of different locust species, historical outbreaks and existing locust and grasshopper operational management systems. Zhang et al. (2019) concluded that the knowledge about locust biology, ecology and the interaction with human-made effects promoting outbreaks of locusts and grasshoppers must be improved; in this way, new and improved methods to forecast and monitor gregarious locust infestations are required.

Recently, Abd El-Ghany et al. (2020) published a review dealing with EO application as a promising strategy for insect pests and diseases management. This review provides a short technical overview of EO sensors and their potential to detect and monitor different insects and agricultural pests.

3.4 Discussion

3.4.1 Contribution of remote sensing to locust management

In this section, we reflect on the main remote sensing contribution for improved locust management and recent trends. First of all, in regards to habitat mapping, recent approach has been shifted from single image land cover analyses (Bryceson, 1989; Sivanpillai et al., 2006; Voss and Dreiser, 1997) towards implementing time series-based classification to generate results for different time steps and thus enable long term habitat and species distribution quantification (Löw et al., 2016; Zhao et al., 2020).

Secondly, in terms of habitat monitoring, there was a district development. In 1991, Cracknell (1991) discussed that the prospect of direct detection of habitats changes are unrealistic or only possible with considerable time lag. In 2002, Crooks and Archer (2002) summarized that soil moisture dataset were not available or restricted to be used on operative base. Looking at the progress in 2008, Maiga et al. (2008) stated that the link between acridian risk and monitored ecological conditions was still relatively empirical at that time. Recent progress in satellite imagery and availability of new datasets in combination with advances in methodological approaches and computing power are about to overcome those restrictions and contribute to a new era in remote sensing-based locust management: using multiple variables at higher temporal resolution and increasing spatial resolution. The introduction of MODIS data and thereafter increase in spatial resolution (250–1000 m), spectral resolution (36 channels) while containing high temporal frequency (daily) and covering large areas contributed to a major boost and improvement in locust management. Since then remote sensing-based research focused on temporal scale and statistical relation of locust occurrence and prior conditions (Pekel et al., 2011; Piou et al., 2013; Renier et al., 2015; Waldner et al., 2015). The observation of vegetation change (greenness maps) over time is one of the most important application in desert locust management (Cressman, 2013; Latchininsky et al., 2016; Piou et al., 2013). According to Piou et al. (2013), especially coherent construction of secondary metrics derived from NDVI time series provides good prediction of desert locust presence and in this way allow a better planning of field surveys (Latchininsky et al., 2016). Furthermore, based on MODIS data, additional vegetation parameters (e.g., EVI, GPP, FPAR, LAI) and variables (e.g., LST) and well-established Analysis-Ready Data (ARD) are provided which have enabled investigation on several important ecological variables and their relation to locust presence. Since then, together with improvement of rainfall estimation and weather prediction, this has been main remote sensing-based components for operative monitoring, early warning and prediction.

Moreover, applications of remote sensing-based soil moisture data have been comparably rare despite the acknowledged fact that it is one of the most important variables defining the survival of locust eggs as well as for the timing of hatching. In 2014, Crooks and Cheke (2014) stated that application of SAR imagery in brown locust forecasting depends on reasonable access to data and useful spatial and temporal resolution for forecasters. In recent years, the addition of soil moisture datasets has been possible due to progress in SAR technology and improved soil moisture algorithms. Recently, Gómez et al. (2019) published a promising approach stating the importance of soil moisture data. The future usage of 1 km soil moisture products in desert locust early warning system at national locust centers and at DLIS-FAO for the entire recession area of the desert locust (0–40 N/20 W-80 E) was introduced by Escorihuela et al. (2018). Additionally, Piou et al. (2019) suggested that soil moisture shall become standard tool for preventive locust management. However, for species with very short incubation time, such as the desert locust, the availability of such datasets needs to be provided in near real time (NRT) to enable appropriate analysis and following measures. This is a challenging task especially regarding the vast areas to be monitored.

In terms of prediction, recent progress utilizes machine learning approaches and establishes statistical relationship between all available and important variables (Gómez et al., 2019; Meynard et al., 2017; Piou et al., 2019). For preventive locust management, forecasting models have to be quickly updated with new satellite data (Piou et al., 2019).

3.4.2 Potential of higher spatial resolution and temporal coverage

Former studies using coarse satellite data stated that there was no significant relation between locust and vegetation indices. Rosenberg (1999) mentioned that by using coarse-spatial-resolution data, it was not possible to identify changes in regions with very low (<5%) vegetation cover, which is typical for desert locust breeding areas. Despland et al. (2004) demonstrated that at continental scale (4° spatial resolution) forecast and outbreak areas are uncorrelated and therefore, they questioned the usefulness of NDVI for desert locust prediction at such a coarse spatial resolution and due to NDVI limitation in arid areas. Tratalos and Cheke (2006) could not identify any linear relationship between locust breeding areas and NDVI (from AVHRR 8 km). Those studies using NDVI at low and medium spatial resolution showed restrictions especially in semi-arid regions and highly fragmented landscapes. Studies utilizing MODIS-based VI at 250 m spatial resolution and temporal relationship proved that there was significant relationship. Nevertheless, despite the improvements introduced by MODIS some restrictions have remained as stated in Cressman (2013), Escorihuela et al. (2018), Renier et al. (2015) and Waldner et al. (2015). There, the authors discuss that satellite data with higher spatial resolution will provide further improvements especially for vegetation detection in arid and semi-arid regions where fragmented vegetation leads to higher commission and omission errors when using coarse resolution data. Waldner et al. (2015) demonstrated an improvement of 20% when comparing MODIS data at 250 m with PROBA-V data at 100 m spatial resolution. The potential of higher-spatial-resolution data has been shown in many other disciplines (e.g., agriculture, forestry, urban development). The utilization, e.g., of Sentinel-1 (available since 2015) and Sentinel-2 (available since 2016) data for monitoring can improve spatial scale and the detection frequency. Peer-reviewed publications which use these data sources for locust research are with one exception (Escorihuela et al., 2018) not available. In addition, a combination of Sentinel-2 and Landsat data can improve the temporal and cloud free observation frequency. The question arises as to whether such datasets can contribute to further significant improvements. Nevertheless, in terms of locust management, one has to keep in mind the usability and feasibility for vast areas in limited resources especially in developing countries. On the one hand, a possible improvement alongside higher spatial resolution needs to be contrasted with time management, reliability and additional required resources and also justify the needs of locust managers. On the other hand, further research can demonstrate improvements and enable operation with further technical and economic development.

Furthermore, using Landsat, and eventually Sentinel data, the detection of damage assessment has been proven to be feasible. Nevertheless, economical loss assessment caused by locust plagues and outbreaks from remote sensing data is still rare (Weiss, 2016). The Landsat archive with data over more than 40 years offers unique opportunities to perform further long-term analysis. For example, systematic damage assessment, vegetation development and quantification related to past large-scale outbreaks can benefit from this data source, although the temporal resolution of Landsat is limited. Long-term analysis and quantification of vegetation structure dynamics as well as land cover and land use change and their relation to locust population dynamics and outbreaks are still rare (Figure 3-6). This fact can be related to high data costs and limited availability before satellite archives were accessible free of charge. Furthermore, locust outbreaks are irregular events and therefore, several studies mostly focus on these specific outbreak years. Nevertheless, research with long-term character is important to investigate the entire range between derived parameters and solitarious and gregarious locust presence. For example, in Tratalos and Cheke (2006), the authors analyzed long NDVI time series to understand whether NDVI is related to different locust phases and population densities or rather to precipitation variability only. Therefore, additional studies covering longer time periods providing a connection between different environmental factors and locust populations might provide new insights.

Finally, the potential and possible benefits of VHR satellites are basically unexplored. Additional studies need to provide a better understanding of how VHR data can be exploited for early warning and detection of early instar activity (e.g., locust bands) and damage assessment. EO data and archives provide the required specifications to tackle these challenges and investigate benefits and restrictions.

3.4.3 Discrepancy between research origin and region of interest

The majority of publications focus on the desert locust and migratory locusts affecting large parts of the African continent, the Arabian Peninsula, India and Pakistan. The third foremost species is the Australian plague locust. For the migratory locust and the Australian plague locust, we found a clear relation between investigated regions of interest and the countries of affiliation of the authors (Figures 3-8 and 3-12). However, there seems to be a gap for desert locust-affected regions as well as for other locust species. One reason is the absence of English-speaking studies despite a wide existing knowledge in affected countries. Additional research is probably available in other languages (e.g., Chinese, French, Russian, Spanish) but is less visible within the English-speaking literature. Furthermore, the absence of English-speaking scientific publications may also be due to the periodic occurrence of locust plagues combined with the fact that many countries and regions have not dealt with these challenges for several decades (Meynard et al., 2020). Moreover, as locust outbreaks are not limited by country borders, more multi-national research on EO applications would contribute to further understanding of locust–human inter-connections as well as for improvement in locust management. Another reason may be the absence of funding to promote further research because locust management is rather pragmatic with the overarching goal in an effective control of outbreaks and not academic publications. Nevertheless, there is still a lack of English-speaking, peer-reviewed literature and studies conducted by organizations or universities located in affected regions. Involving local stakeholders with their knowledge and experience, would definitely contribute to a further development and to an improved exploitation of EO capacities for locust management and research.

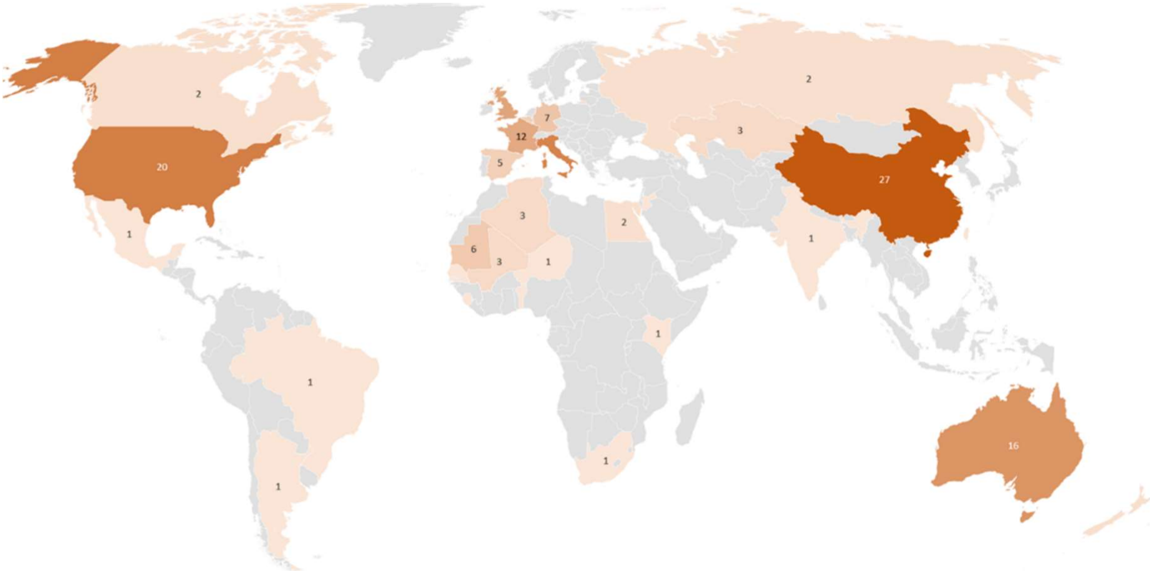

Figure 3-12. Country of origin of authors' affiliation.

3.4.4 Overall lack of remote sensing application for locust and grasshopper species

Despite the progress been made for the desert locust, the migratory locust and the Australian plague locust (shared total of 74%), there is a lack of studies for other pest locust species (Figure 3-7). This lack has been documented in previous studies and is also related to less advanced or absent organized preventive locust management (Latchininsky et al., 2016; Latchininsky, 2013). In our review, we quantify the actual rate of conducted studies which reveals the unequal distribution for other species not only because of absence of operative management but also in conducted research. Since Latchininsky's review in 2013 (Latchininsky, 2013) the progress and investigation for other locust species remained minor. Therefore, the question arises as to whether remote sensing datasets and applications might be insufficient to map and monitor variables of importance due to more complex environment or is the lack of studies because of restricted funding or academic resources dealing with other locust species? Based on developments and encouraging results for the desert locust, the migratory locust and the Australian plague locust, research and management for other species could benefit from further remote sensing-based applications. Studies over the last four decades provide a good foundation. Nevertheless, field observations and extended species-specific ecological and biological knowledge are crucial to achieve meaningful results when applying remote sensing.

3.4.5 Potential of alternative methods and analysis

Recent studies focus on comprehensive analysis of several essential ecological variables. This is due to the availability of more and more ARD. In this way, scientist can focus on the relation and individual importance of variables rather than dealing with extensive raw data preprocessing. Reviewed studies have been applying mostly NDVI to assess the risk of gregarization, to predict hatching and outbreaks, or simply use the technique as a metric for land cover classification. However, the capacity of NDVI in arid areas has been controversial. Therefore, at the background of new options and cloud computing possibilities, the benefit of additional indices or variables can be explored and compared. For example, Cherlet et al. (1991) concluded that results achieved using PVI were most reliable. However, the operative usability at a large scale was not feasible at that time. Here the question arises as to whether application of other indices can provide significant improvement or not. At the background of previous discussion and findings following investigations focusing on additional strategies to prove improvements or limitations can be addressed:

- Further research on geomorphological variables for the desert locust as suggested by Lazar et al. (2015).
- Application of sensor fusion/combination to minimize restrictions of sensor characteristics (Knauer et al., 2016; Orynbaikyzy et al., 2019).
- Application of hyperspectral data to enable more detailed classification of vegetation types, stressed vegetation or damage (Bradley, 2014; Holzwarth et al., 2020).
- Time-series analysis focusing on phenology (Eklundh and Jönsson, 2015; Stanimirova et al., 2019; Verbesselt et al., 2010).
- Other indices and metrics, e.g., Soil Adjusted Vegetation Index (SAVI) (Despland, 2003) or Perpendicular Vegetation Index (PVI), which specifically consider ‘noise’ caused by soil (Jensen, 2008). The question is, can other approaches or indices overcome restrictions which are observed in arid regions when using NDVI?
- As shown by Propastin (2012, 2013) altimetry data in combination with VI show high potential for monitoring migratory locust habitats along rivers and lakes. In this context the new Surface Water and Ocean Topography (SWOT) mission as well as other altimetry datasets can contribute to further monitoring improvement for migratory locust species.
- Systematic and large-scale detection of damage and remote sensing-based economical loss assessment studies to evaluate economic impact and production loss on large scale. Remote sensing applications have received comparable little attention (Weiss, 2016). Red edge channel, e.g., from RapidEye satellites which was developed specifically to identify damaged or stressed vegetation could provide improved results for loss assessment of green vegetation (Kross et al., 2015). The

question is, can remote sensing-based damage assessment contribute to economic loss estimation on larger scale?

- Usage of VHR resolution imagery and machine learning approaches (Hoeser et al., 2020; Hoeser and Kuenzer, 2020; Kattenborn et al., 2021; Ye et al., 2020) to investigate the benefit in early locust damage and locust band detection. The question is, can dense locust bands be identified in VHR imagery?
- Further inclusion of remote sensing in ENM and HSI modelling, where all important static and dynamic environmental parameters are combined with species specific preferences (Geng et al., 2020; Walz et al., 2015; Warren et al., 2016; Zajac et al., 2015).
- The importance and potential of UAV-based systems for locust management supporting ground teams requires standardized analysis and investigation for automatic image processing. The advantages of UAV-based monitoring are promising (Radoglou-Grammatikis, 2020; Tsouros et al., 2019). However, scientific evidence of benefits within locust management and research are still rare. Monitoring of vegetation state, damage assessment as well as monitoring of locust bands are possible fields for investigation. The question here is, how can UAV-based monitoring applications contribute to operative locust management?
- Finally, locusts and grasshoppers strongly depend on climate conditions such as temperature, precipitation and humidity (Tronin et al., 2014). Further research to analyze the influence of climate and environmental change to different locust species distributions and outbreak risk are therefore required (Meynard et al., 2020).

Mentioned suggestions for further research have to prove their benefit and outline practical contribution towards locust management. Therefore, from a locust management perspective, one has to consider all important factors within operational services (e.g., internet connection, access to data and applicability, area to be monitored, reliability vs. spatial precision) and contrast it with possible improvements.

3.5 Conclusions

In this review, we provided an extensive overview of 110 English-speaking, EO-related research articles with respect to destructive locust/grasshopper pest species. On the one hand, our focus was to quantify different aspects of reviewed studies. Therefore, we categorized the studies covering (i) investigated species, (ii) areas of interest, (iii) sensor types employed, and (iv) variables used. On the other hand, we aimed to point out main research foci and reflect on the development. We categorized specific research foci, namely (A) habitat mapping, (B) habitat monitoring, (C) outbreak/hatching prediction, (D) damage and loss assessment, and (E) review and general studies. By looking at the quantified results and methodological progress, the following findings can be summarized:

- Investigated species: The majority of studies focused on the desert locust (33%), the migratory locust (27%) and the Australian plague locust (14%). Remote sensing applications for other harmful locust species such as the brown locust (4%), the Central and South American locusts (1%), the Italian locust (5%), the Moroccan locust (1%) or the red locust (1%) are still very rare.

- Areas of interest: Areas of interest were mostly located in China (24%), Australia (14%) and Mauritania (11%). Despite a high risk of outbreaks from different species, there is a lack of English-speaking studies for the Arabian Peninsula (none), the Middle East and Pakistan (none), India (1%), South-East Asia (1%), North and South America (2%) and Russia (2%).
- Employed sensor types: Optical EO data were most frequently used. Here, 57% of all studies solely used optical data. Whereas, AVHRR, MODIS, SPOT-VGT and Landsat sensors were mostly employed. Following optical sensors, radar (6%) and TIR (3%) were the second and third most used sensor types, respectively. However, both were mostly applied in combination with others (optical/radar 10%, optical/radar/TIR 5%, radar/TIR 5%, optical/TIR 3%). No peer-reviewed publication was found using VHR (e.g., Quickbird, IKONOS, WorldView) or Sentinel-2 data; only one study is available using Sentinel-1 SAR data.
- Used variables: The majority of studies applied NDVI, land cover information, LAI or fCover for analysis (39%, 13%, 5%, 4%), referring to the importance of vegetation as a key parameter affecting population density and phase change of locusts. Despite the high importance of soil moisture for locust development, there are only few studies focusing on EO-based soil moisture retrieval (9%). However, recent development indicates that remote sensing-based soil moisture data will be an essential part in further research and eventually in desert locust management.
- Research foci: The majority of studies focused on habitat monitoring (39%), followed by habitat mapping (25%), outbreak/hatching prediction (17%) and general review publications (10%). Few damage assessment studies were conducted (9%); most of these studies are feasibility cases carried out for the migratory locust in selected geographic areas.
- Most articles reveal test case studies covering small study regions and short time periods. Overall, only 18 studies were long-term covering ten or more years.
- Furthermore, we found fewer English-speaking, peer-reviewed literature and studies conducted by organizations or universities located in locust-affected regions (except Australia and China).

The role of remote sensing for locust management and research has increased over the past 40 years and nowadays can be considered as irreplaceable. Well-operating monitoring and prediction systems for the desert locust (by FAO) and the Australian plague locust (by APLC) document the success and the advantage of implementing EO data to save time and resources once outbreaks occur. Summarizing, most EO applications focus on the monitoring of vegetation changes and precipitation patterns in locust habitat areas to determine potential gregarization, to stratify field surveys and to assess the risk of locust population increase (Deveson, 2013). In recent years, scientific attention was paid to soil moisture retrieval as well as modelling approaches combining several important variables. In terms of vegetation and land cover monitoring, the trend shows more time-series applications focusing on phenology and replace single image analysis. Overall, this review underlines further needs for EO-based research to either fully exploit the potentials of EO data and approaches or proof their limits. There is a lack of studies using available open source EO data archives over entire habitats and long time periods. Moreover, the sensors of the Sentinel fleet are still rarely applied. Here, experience from other disciplines, e.g., agriculture and forestry, may be adopted to improve results and eventually contribute to locust management. Feasibility and test case studies have played a crucial role to contribute to nowadays operative services. Applications which were unimageable a few decades ago have become operative along with technological development in terms of sensor characteristics, methodologies and computing power. Many countries launch and operate environmental and industrial satellites. Fusion and combination of available data sources might enable to detecting the Earth at very high spatial, spectral and temporal resolution. Today, the Earth is covered by VHR data from different satellites sources. Therefore, detection of locust bands might become more feasible in future. Nevertheless, extensive knowledge of considered species and geography remains a key factor in further locust-related remote sensing applications. Therefore, more inter- and multi-national research funding utilizing the full capacity of remote sensing data is required.

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CHAPTER 4

4 Predicting suitable breeding areas for different locust species – A multi-scale approach accounting for environmental conditions and current land cover situation

Abstract

In this study, we present a fused multi-scale approach to model habitat suitability index (HSI) maps for three different locust species. The presented methodology was applied for the Italian locust (Calliptamus italicus, CIT) in Pavlodar oblast, Northern Kazakhstan, for the Moroccan locust (Dociostaurus maroccanus, DMA) in Turkistan oblast, South Kazakhstan and for the desert locust (Schistocerca gregaria) in Awash river basin, Ethiopia, Djibouti, Somalia. The main novelty is based on implementing results from ecological niche modelling (ENM) with time-series analyses of high spatial resolution remote sensing data (Sentinel-2) and further auxiliary datasets in a fused HSI model. Within the ENM important climatic variables (e.g. temperature, rainfall) and edaphic variables (e.g. sand and moisture contents) are included at a coarse spatial resolution. The analyses of Sentinel-2 time-series data enables mapping locust breeding habitats based on recent remotely sensed land observation at high spatial resolution and mirror the actual vegetation state, land use, land cover and in this way identify areas with favorable conditions for egg survival and breeding. The fused HSI results for year 2019 were validated based on ground field observation and reach area under curve (AUC) performance of 0.747% for CIT, 0.850% for DMA and 0.801% for desert locust. The innovation of this study is a multi-scale approach which accounts not only for climatic and environmental conditions but also for current vegetation and land management situation. This kind of up-to-date spatial detailed information on breeding suitability could enable area prioritization for risk assessment, monitoring and early intervention of locust pests.

4.1 Introduction

Since the beginning of land cultivation locust outbreaks, and plagues have been a danger to the human population worldwide and often brought devastation, hunger and death (Zhang et al., 2019). All continents except for Antarctica have been infested by different locust species, which are capable to affect the livelihood of approximately 10% of the global population (Latchininsky and Sivanpillai, 2010). Recently, swarms of desert locusts (*Schistocerca gregaria*) endanger food security across East Africa, the Arabic peninsula, India and Pakistan (Meynard et al., 2020). Other species e.g. Italian locust (*Calliptamus italicus*, CIT) and Moroccan locust (*Dociostaurus maroccanus*, DMA) can also cause massive devastation at regional and local scales (Kambulin, 2018; Latchininsky, 1998; Le Gall et al., 2019; Reuters, 2019; Toleubayev et al., 2007). In gregarious phase, locusts can damage crops and pasture massively, since they eat an equivalent of their body mass in green vegetation every day (Steedman, 1990; Uvarov, 1957). The loss of biomass is not only of economic importance, but also endangers food security, livestock and other fauna species. Furthermore, plants themselves are harmed and inhibited in natural regeneration due to the consumption of seeds and sprouts by locust bands (Kambulin, 2018). Nevertheless, in solitary phase, locusts are a beneficial part of an ecosystem by facilitating nutrient cycling and playing an important role in the food chain (Tsychuyeva et al., 2017). Unusual weather conditions, subsequent droughts and scarcity of plant food force the insects to aggregate, initiating the gregarious phase in which locusts create bands and form highly mobile flying swarms of adult insects (Kimathi et al., 2020; Meynard et al., 2020). Locust population densities or states are commonly distinguished by the definitions of outbreak, plague or pest, decline and recession (Cressman, 2016).

Countries at risk of locust outbreaks usually possess regional and national monitoring systems. The Australian Plague Locust Commission (APLC) operates successfully by implementing weather forecast, remote sensing and ground observation (Hunter, 2004; Hunter et al., 2008). The Food and Agriculture Organization (FAO) of the United Nations operates the Desert Locust Information Service (DLIS) in close cooperation with involved countries (FAO, 2009). Furthermore, similar efforts are made for Central Asia and the Caucasus region where Italian, Moroccan and Asian migratory locusts have to be monitored and controlled (FAO, 2021a). One of the major goals of locust monitoring is assessing the geographic extent of possible breeding areas, highlighting gregarization hotspots, evaluation of population parameters and accordingly initiating control activities. Despite the danger of gregarious locusts for food security, the ability to predict and manage locust outbreaks is still insufficient (Latchininsky, 2013). Detailed spatial knowledge about locust habitats and suitable breeding areas with high probability of eggs surviving are of major importance for regional and national plant protection and locust monitoring organizations because it demands a lot of financial means, manpower and time. In this context, remote sensing data and applications proved great potential as an additional source because they perform efficient, more economical, with less manpower and are regardless of national borders (Kambulin, 2018). Since the 1970s remote sensing data are used e.g. for locust habitat mapping mainly for the desert locust, migratory locust and Australian plague locust but with only very few studies for CIT and DMA (Klein et al., 2021; Latchininsky et al., 2016; Latchininsky, 2013). Sivanpillai et al. (2009) applied IRS-S WiFS data with 56 m spatial resolution for a habitat model of CIT in the north-east of Kazakhstan. The results were promising and the authors identify the benefit of higher spatial resolution satellite data. Latchininsky (2013) states the importance of model development for habitat mapping of CIT and DMA but saw the research still in the initial phase. Recent modelling applications on locust species distribution, ecological niche and habitat suitability present continuous development (Aragón et al., 2013; Gómez et al., 2018, 2019; Kimathi et al., 2020; Malakhov and Zlatanov, 2020; Piou et al., 2013, 2019; Veran et al., 2015). Availability of new datasets (e.g. soil moisture (Escorihuela et al., 2018; Piou et al., 2019)), methods and technological progress contribute to this steady improvement. For example, Ecological Niche Models (ENM) are based on machine learning algorithms to predict suitable habitats from datasets describing environmental conditions and species presence and absence records. Within the ENM important climatic variables such as temperature, rainfall and edaphic variables such as sand, moisture contents are included at a coarse spatial resolution from up to 1 km. The modelled results provide suitable areas at a larger geographic scale but usually do not discriminate higher spatial detail or account for land cover related characteristics. Nowadays, open source remote sensing data and cloud computing provide additional opportunities for modelling and monitoring of locust risks. Especially the use of temporally dense and high spatial resolution satellite data (e.g. Sentinel-1 and -2, Landsat) in combination with climate and environmental data can enable prediction in vulnerable areas with a high level of detail.

In this study, we present an approach based on habitat suitability index (HSI) model which takes advantage of different environmental variables, including ENM results, time-series analyses of satellite data and species-specific knowledge to better discriminate areas providing optimal locust breeding and egg-pod incubation conditions. For the ENM we utilized up-to-date data from TerraClimate to account for recent climate conditions of last 20 years. Current vegetation state and land management conditions are targeted by the analysis of Sentinel-2 data. Additionally, unique species-dependent favorable and excluding conditions were considered. We applied the approach for three different locust species to demonstrate the advantages and challenges and, in this way, contribute to further development in this field. The study is conducted for CIT in North Kazakhstan (Pavlodar oblast), for DMA in South Kazakhstan (Turkistan oblast) and for desert locust in the Awash river basin (ARB), Ethiopia, Djibouti, Somalia. The results are validated with ground truth data collected by local organizations.

4.2 Background information on locust species and study areas

4.2.1 The Italian locust and Pavlodar oblast

The Italian locust was the first of all locust species recorded as a great pest in Russia in the year 1008 (FAO, 2021a). The species' distribution area stretches from Western Europe across meadow steppes in Central Asia, Mongolia and West Siberia (Kambulin, 2018; Latchininsky, 2013). Although CIT is on the red list of endangered species in northern Europe, it is a threatening pests in Russia, Central Asia and the Caucasus (Latchininsky, 2013; Sergeev and Van'kova, 2008). Generally, the species can be found in arid steppes and semi-deserts, preferring vegetation such as wormwood and sagebrush (Artemisia spp., Monard et al., 2009). In addition, human-affected areas such as field borders, fallow fields and road edges can provide favorable conditions (Kambulin, 2018; Latchininsky, 2013; Sergeev et al., 2016). In such areas, CIT as herbivore inhabits fallow fields, field borders, waste lands and neglected orchards or Lucerne meadows, sometimes with saline soil (Sergeev et al., 2016; Sergeev, 2021). The insects are also common close to irrigated crops and tolerant to a wide range of semi-arid soils and climate conditions. CIT as an ecological plastic species is generally not as fastidiously as other locusts and can occupy a wide range of habitats, especially during outbreaks (Monard et al., 2009). It disappears completely if land is plowed since plowing leads to mechanic destruction of egg-pods. The occurrence of CIT is not only related to food preferences, but also to physical soil properties. Moderate compact sandy soils are more favorable than very loose or compact soils and facilitate oviposition (Toleubayev et al., 2007). Breeding, mating and egg-laying occur in the period between June and September. Since temperature drops during the winter period, the egg-pods lie dormant in diapause. Once moisture is introduced during the warming period in spring, the incubation period starts. Finally, hatching occurs from late April to June, with higher temperatures and lower precipitation during this period generally resulting in higher populations. Once ecological conditions are highly suitable over a multiple-year period, a high density of egg-pods and strong survival rates can lead to higher density of adult individuals, potentially leading to phase change, and thus to outbreaks (Sergeev and Van'kova, 2008).

The first study area is the administrative area of Pavlodar oblast, located in the North-East of Kazakhstan (Figure 4-1A) with a total area of 125,000 km². Winters are long (5.5 months) and summers are short (3 months). About 70 to 85% of annual precipitation (200 to 400 mm) falls over the winter period. Characteristically for steppes and semi-desserts, large areas of Kazakhstan are dominated by herbaceous vegetation and sparse shrubs or herbaceous vegetation. Between 1953 and 1964 vast areas of untouched steppe in Northern Kazakhstan were converted to agricultural fields which led to far-reaching consequences and was one of the major land use changes worldwide during the 20th century (Frühauf and Meinel, 2007). Due to the climatic conditions in Kazakhstan, it can take up to 25 years for fallow land to return to its original grassland state (Latchininsky, 2013). After the break down of the USSR in 1991, formerly cultivated land was abandoned, since Kazakhstan lost its role of grain producer for the USSR (Monard et al., 2009) and areas for cereal production decreased from about 25 to 12 million ha (Toleubayev et al., 2007). Those fallow lands became perfect habitats for CIT and have led to a population increase starting in 1996 and leading to the great plague in 1998-2000 (Toleubayev et al., 2007).

4.2.2. The Moroccan locust and Turkistan oblast

The Moroccan locust occurs in many parts of the Mediterranean and Central Asia. Within the steppe, DMA has rather specific requirements for suitable breeding habitats. They prefer habitats located in elevated regions and foothills (Kokanova, 2017; Latchininsky, 1998, 2013; Monard et al., 2009). In such an environment, hard and dry soils with a high clay content are preferred for egg-laying (Latchininsky, 1998; Uvarov, 1957). Especially areas with a mosaic of steppe vegetation and dry bare soil are preferred, because vegetation clumps protect the egg-pods with shade and provide food for nymphs after hatching (Baldacchino et al., 2012; Monard et al., 2009; Uvarov, 1957). Such mosaics are often found in overgrazed fields, which form threatening breeding hotspots for DMA (Latchininsky, 1998; Monard et al., 2009; Uvarov, 1957; Zhang et al., 2019). Comparable to the Italian locust disturbed soils (i.e. regularly plowed soil in active agricultural fields) are highly unsuitable for DMA's breeding, because the egg-pods are destroyed there (Latchininsky, 1998; Monard et al., 2009). Areas that are relatively wet or moist, highly vegetated or have no vegetation at all are rather unsuitable habitats for DMA (Baldacchino et al., 2012; Latchininsky, 1998). In terms of climatological conditions, DMA occurs in regions that receive 300-500 mm of yearly precipitation (Latchininsky, 2013; Monard et al., 2009) and spring precipitation of approximately 100 mm (Kokanova, 2017; Uvarov, 1957). The mean annual temperature in their breeding habitats is around 16°C (Kokanova, 2017). Although DMA was considered as one of the most dangerous agricultural pests in the Mediterranean and Central Asia, the species' population has decreased during the last century, especially due to industrial, agricultural and urban developments (Latchininsky, 1998). Land cultivation has a negative impact on DMA breeding habitats and many populations have disappeared because of intensive agricultural developments (Monard et al., 2009). However, in Central Asia the danger is still serious. New agricultural development of formerly virgin dry steppes in Azerbaijan, Turkmenistan, Uzbekistan and Kazakhstan resulted in the vicinity of DMA breeding areas and newly-grown crops, which severely increased the risk of crop damage caused by DMA (Monard et al., 2009). Same as CIT, the DMA is an univoltine species (one generation per year), with winter egg diapause. After winter diapause, egg hatching occurs from February to April.

The second study area is the administrative area of Turkistan oblast, located in the South of Kazakhstan (Figure 4-1B) and a total area of 117,000 km². Turkistan oblast is characterized by a semi-arid climate and consists mainly of sparsely vegetated grass-, shrub- and croplands. The area has a high range of altitudes, with 120 m of elevation in the lower areas and 3800 m in the mountainous regions in the south-east. Annual precipitation usually ranges from 100 to 500 mm, with more rainfall especially at higher altitudes and during the winter period. The region serves as a suitable habitat for DMA because of the many semi-arid dry grass- and shrublands. Infestations have occurred regularly, especially with relatively hot and dry spring seasons (Latchininsky, 1998).

4.2.3. The Desert locust and Awash river basin

The desert locust is the most dangerous of all migratory pest species in the world (Cressman, 2016). In solitarious phase, desert locust are found in deserts of North Africa, the Middle East and Southwest Asia covering approx.16 Mio km² of so-called recession area (Cressman, 2016). Within these regions there are summer and winter-spring breeding areas. Gregarization of desert locust highly depends on sporadic and unusual heavy rains in the recession area. On the contrary to CIT and DMA, the desert locust does not have a diapause during a cold season and several successive generations can follow one after another when ecological conditions are optimal.

The third selected study area is the Awash river basin (ARB) which extends over its riparian countries Ethiopia, Djibouti, and Somalia with a size of approx. 108,000 km² (Figure 4-1C). In general, the climate in ARB is closely linked to elevation (Bretzler et al., 2011). The rainfall distribution is bimodal in the middle and lower basin and unimodal in the upper basin. The mean annual rainfall is 850 mm over the western part and 465 mm over the eastern part of the basin. Annual rainfall is related to Intertropical Convergence Zone (ITCZ) and surface temperature variation over the Indian Ocean and is therefore highly variable resulting in extreme events such as floods or droughts (Dessu and Melesse, 2012; Edossa et al., 2010). The ARB is located within recession area of desert locust and areas of primary breeding can be found here. In 2019, eight tropical cyclones developed over the Indian Ocean resulting in heavy rains over the ARB, which led to suitable conditions for desert locust breeding (Salih et al., 2020).

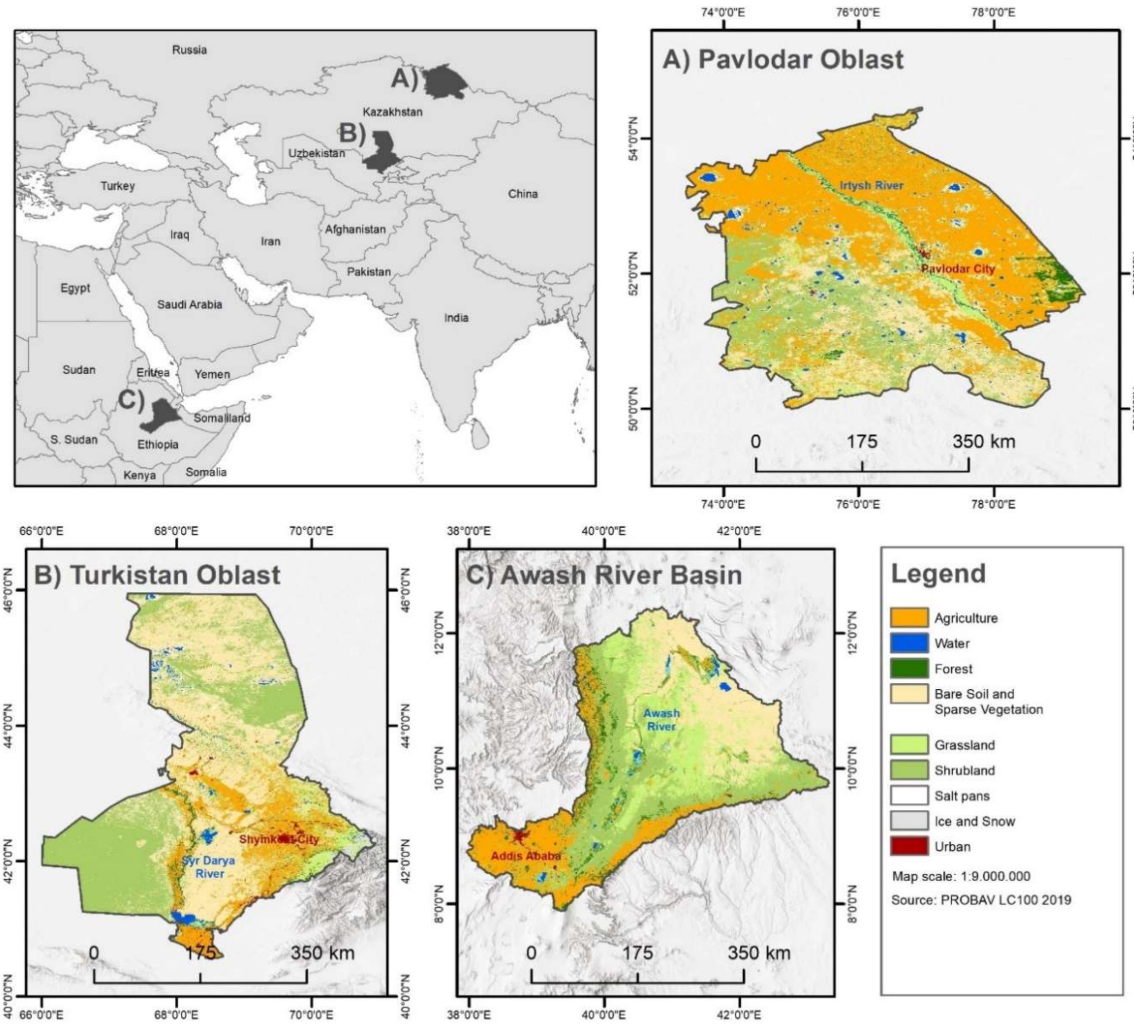

Figure 4-1. LCC and locations of three tests sites. A) Pavlodar oblast for Italian locust, B) Turkistan oblast for Moroccan locust, C) Awash river basin for desert locust.

4.3 Materials and methods

In this section, we introduce the methodological concept, used data and justification at the background of each species and their preferable conditions. The approach is based on three main steps. First, based on literature review, environmental conditions and corresponding geospatial datasets essential for selected locust species breeding suitability were identified. Second, we apply ENM using climatic, static edaphic and vegetation variables to generate the distribution of ecological niche for each species. ENM is usually conducted on a larger scale using climatic data with a spatial resolution of 1 km or coarser. In such modelling efforts, small-scale spatial details which can be quite heterogeneous are not considered. Therefore, in a third step, we fuse the ENM results and additional variables representing higher spatial detail and recent land surface conditions within an HSI model to gain higher spatial detail and addressing current landscape heterogeneity.

The HSI is a methodological approach to model environmental preferences or limitations for organisms and is an estimator of habitat support (Walz et al., 2015). HSI models were developed by the United States Fish and Wildlife Service in 1981 (Wakeley, 1988) as a cost-effective, powerful and dynamic management tool (Zajac et al., 2015). Literature reviews, expert knowledge and field data can be used to measure different indices for habitat variables, which are then ranked in a HSI model. After Warren et al. (2016) expert knowledge based models perform similarly to empirical models and can be optimized with input of field data to improve their predictive power. The identification of key variables is the most crucial element in HSI modeling (Hirzel and Le Lay, 2008). A schematic overview of the entire workflow including relation of different datasets and models is presented in Figure 4-2.

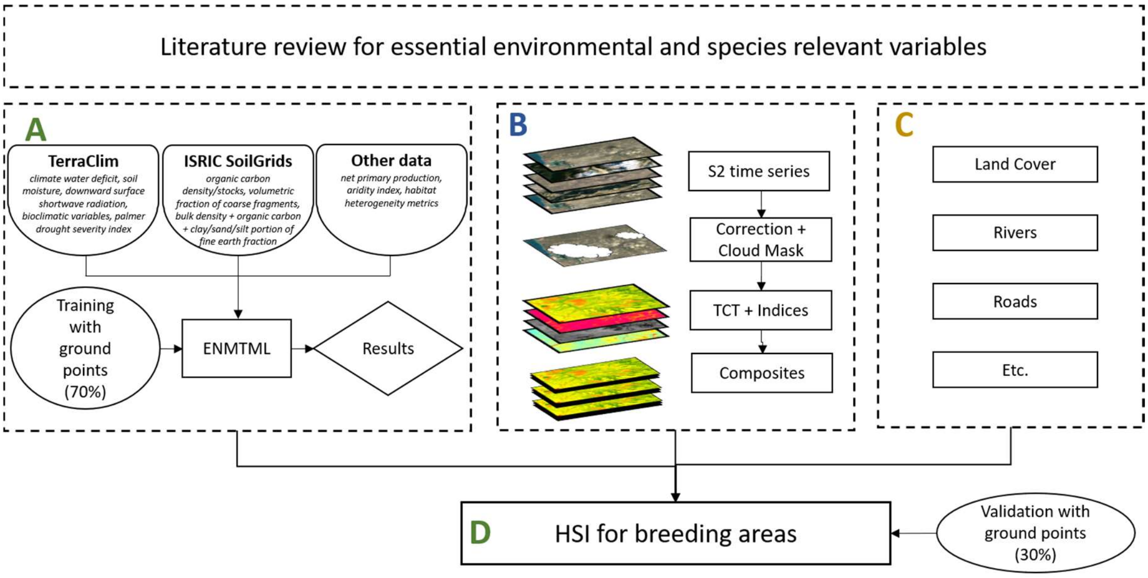

Figure 4-2. Schematic workflow of the presented approach.
A) ENM, B) Sentinel-2 based analysis of land surface conditions, C) Additional static variables which can be used as excluding factors depending on species, D) Final HSI model. (ISRIC = International Soil Reference and Information Centre; ENMTML = Ecological Niche Model R package (Andrade et al., 2020); TCT = tasseled cap transformation)

4.3.1 Datasets and variables for ecological niche and habitat suitability index models

4.3.1.1 TerraClimate

Climate data includes fundamental descriptors for almost every species' niche. A commonly used dataset for species modeling is WorldClim (Kimathi et al., 2020; Malakhov and Zlatanov, 2020), that comes with averaged monthly information based on long term data between 1970 and 2000 (Fick and Hijmans, 2017). In this study, we decided to utilize TerraClimate (Abatzoglou et al., 2018) dataset to account for the more recent time period at a spatial resolution of 1/24th of a degree (approx. 4.6 km at the equator). Besides usual variables such as maximum and minimum temperature, vapor pressure, precipitation accumulation, solar radiation and windspeed, the dataset includes further variables such as reference evapotranspiration (ASCE Penman-Montieth), runoff, actual evapotranspiration, climate water deficit, soil moisture, snow water equivalent, Palmer Drought Severity Index, and vapor pressure deficit. We calculated the bioclimatic variables (bio2, bio3, bio4, bio7, bio15) using the processing methodology of the WorldClim dataset and the TerraClimate input variables for the time between 2001 and 2019 within the Google Earth Engine (GEE) application (Gorelick et al., 2017). The main reasons to utilize TerraClimate were the availability of consistent soil moisture data and more recent data in general, which allowed considering an eventual change in climate variables over the last two decades for mapping an up-to-date breeding habitat.

4.3.1.2 Additional static datasets

While soil moisture information is retrieved via the TerraClimate dataset, several static soil properties have to be considered. Therefore, variables from SoilGrids 2.0 dataset, which is provided by the International Soil Reference and Information Centre (ISRIC), were included. The ISRIC SoilGrids 2.0 provides information on six standard depths (up to 2 m) with a spatial resolution of 250 m for soil type, density, and other soil properties (Poggio et al., 2021).

Additionally, we included seasonal Net Primary Productivity (NPP) product to benefit the ENM (Leitão and Santos, 2019). The MODIS-NPP dataset for 2001-2019 is available at 500 m spatial and 8-day temporal resolution and was aggregated and processed into four seasonal composites (Jan-Mar, Apr-Jun, Jul-Sep, Oct-Dec).

Furthermore, we included a landscape texture/heterogeneity dataset (Tuanmu and Jetz, 2015). It is calculated as an average over the period of 2001 until 2005, using 30 m Enhanced Vegetation Index (EVI) input data at a spatial resolution of 1 km.

4.3.1.3 Water accumulation layer

This layer is based on topographic features and was created by detecting small scale runoff areas, that include seasonal watercourses, which are also known as Wadis. The Wadis become suitable for desert locust breeding when a sufficient amount of rainwater accumulates (Lazar et al., 2015). The processing was based on the Python package pysheds (Bartos 2020), which enables deriving flow accumulation areas from DEMs (ALOS World 3D - 30m (AW3D30), (Takaku et al., 2020)).

4.3.1.4 Sentinel-2 multi-spectral data

The primary dataset that was used to derive actual land surface conditions was optical satellite imagery from Sentinel-2A and -2B. Sentinel-2 images were selected covering the entire study areas of Pavlodar oblast (in total 24 Sentinel-2 tiles), Turkistan oblast (in total 24 Sentinel-2 tiles) and ARB (in total 28 Sentinel-2 tiles) for the years 2017 to 2020. The Sentinel-2 raw data was downloaded and corrected for atmospheric effects with sen2cor software (Pflug et al., 2020) and cloud masking was conducted with the Fmask algorithm (Zhu et al., 2015). Images with a cloud cover larger than 50% were excluded from the analysis. For all three regions, a total of 4,946 single images (6.76 TB) was downloaded and pre-processed for further analyses. Top of Atmosphere (TOA) reflectance was converted to

Bottom of Atmosphere (BOA) reflectance. Additionally, an automatic classification included several classes (water, clouds, shadow, ice, no data). Based on BOA data, Tasseled Cap Brightness (TCB), Greenness (TCG) and Wetness (TCW), as well as the Perpendicular Vegetation Index (PVI) which required a regional definition of soil line (Jensen, 2008), was derived. Since, the application of NDVI in semi-arid regions comes along with restrictions and saturation effects (Cherlet et al., 1991; Despland et al., 2004; Pekel et al., 2011), we used PVI as an alternative. The PVI uses the perpendicular distance to the soil line as an indicator of plant development while considering noise caused by soil (Jensen, 2008). Soil properties influence the radiometric response of canopies or vegetation detected by indices since the soil is the last background. Especially for sparsely vegetated areas, which are typical habitats of several locust species in steppe or semi desert, a vegetation index considering the influence of soil is advantageous (Baret et al., 1993).

$$PVI = \frac{NIR - a * RED - b}{\sqrt{1 + a^2}}$$

with NIR as near infrared reflection, RED as red reflection, a as slope and b as intercept of the soil line. The soil line concept builds on a linear relationship between red and near infrared reflectance of bare soil and aims to remove most of the effects of soil reflectance for vegetation applications (Baret et al., 1993). The input of this regression is soil reflectance, which is extracted from several parts of bare soil samples within the respective study area as soil reflectance varies from region to region mainly depending on the soil type. Despite all efforts to determine a global soil line, it is advised to delineate study site-specific parameters. Therefore, bare soil samples were manually extracted for each study region to account for their specific soil conditions.

4.3.1.5 Pre-processing for spatial and temporal aggregation

Since most used datasets are characterized by different spatial and temporal resolution, pre-processing steps aiming spatial and temporal aggregation were necessary. The datasets which are used for ENM require identical spatial extent and resolution (Figure 4-2A, (Andrade et al., 2020)). Here, the dataset with the coarsest pixel is taken as reference and all other datasets were upscaled by the means of bilinear interpolation approach. Since all dataset used for the ENM are available on global scale, a subset for each study domain was possible. Furthermore, the temporal frequency of all datasets had to be considered. Here, all datasets with higher temporal frequency were aggregated to monthly, seasonal and annual composites (e.g. bio2, bio3, bio4, bio7, bio15). The time-series analysis and pre-processing of Sentinel-2 data is described in section 3.1.4. In regards to spatial resolution within the HSI model, the original Sentinel-2 pixel size and projection are maintained.

4.3.1.6 Reference data

Reference data for CIT and DMA breeding locations were acquired in field surveys by regional authorities and provided within the Locust-Tec project for the years 2016-2020. In this study, we consider only location of detected early instar hoppers which mirror successful egg incubation and nymph hatching. In total, 2,985 locations of DMA and 671 locations for

CIT were registered by local locust monitoring offices. Besides coordinates, the offices usually record different quantitative and qualitative parameters. However, for this study only geolocations of early hopper stages were used as points of occurrence.

For desert locust, we used free accessible data published by FAO in the Locust Hub (FAO, 2021b). Here, only breeding locations as well as sightings of early nymph instar were selected for the entire available time period (1985-2020) resulting in a total of 238 occurrence points within ARB and 3,617 for the larger domain of East Africa and the Middle East. Symmons and Cressman (2001) state, that the first four instar levels of desert locust hopper development have a duration of approx. six to seven days. Depending on the weather conditions and the vegetation cover, the daily displacement distances of desert locust hoppers during the first instar vary between 25 and 100 meters (Symmons and Cressman, 2001). Because of the low displacement distance during this early phase of locust development, the underlying assumption is that the actual location of hatching was in the close surrounding (Ellenburg et al., 2021). The combination of early instar hopper sightings and actual breeding locations is a reasonable method to increase the number of observations for further training and validation. The reference data for each species were then randomly split for training the ENM (70%), and for validation (30%). Pseudo-absence points were generated within ENM process (section 3.2).

4.3.2 Ecological niche modelling

According to (Peterson, 2006), environmental (or ecological) niche modelling is the characterization of the distribution of a species in ecological space, which can be used to determine the potential distribution of a species in geographic space. In this context, known occurrences of a species can be related to landscape features and climatic conditions to predict unknown occurrences. Generally, the environmental niche of a species is considered to consist of three components: abiotic conditions (e.g. temperature, humidity, soil type), biotic conditions (e.g. species interactions, predation, invasion), and accessibility which describes non-biotic conditions limiting the actual dispersion of a species within its potential range (Peterson, 2006). For this study, the R software package ENMTML was used to construct the ENMs for three species of interest (Figure 4-3). The ENMTML package considers a wide variety of parameters and modelling algorithms that have been identified as highly influential to the process of ENM by leading scientists in the field (Andrade et al., 2020). In fact, choosing different model algorithms has been shown to have a minor effect on model outcome than adjusting assumptions and their related parameters such as pseudo-absence selection (Senay et al., 2013). The package includes a selection of up to 13 algorithms for the correlation of input variables to presence and pseudo-absence records (e.g. Boosted Regression Trees, Domain, Generalized Additive Models, Bayesian Gaussian Process, Generalized Linear Models, Maximum Likelihood, Maximum Entropy default, Maximum Entropy simple, Random Forest, Support Vector Machine). In case collinearity reduction methods are chosen, corresponding variables are removed with a high degree of collinearity. The selected collinearity reduction approach was the widely used Variance Inflation Factor (VIF). Second, using the provided occurrence data, also called ‘presence’ records, the input variables were extracted at the locations of the presence points. The occurrence points were ‘thinned’, by removing points which occur within a specified distance to one another to reduce spatial autocorrelation effects (Aiello-Lammens et al., 2015). In order to further mitigate the effects of spatial auto-correlation, a spatial portioning method was chosen for model training. This ensures that training and validation points are not located in immediate vicinity. The method of generating pseudo-absence points was a random selection outside a geographic buffer of 10 km. The final model output is based on an ensemble of all available and applicable algorithms as it usually provides the best performance compared to single approaches. The weighted mean (W-MEAN) was used as a model ensemble method, which incorporated the True Skill Statistic (TSS) measure of model performance as weights.

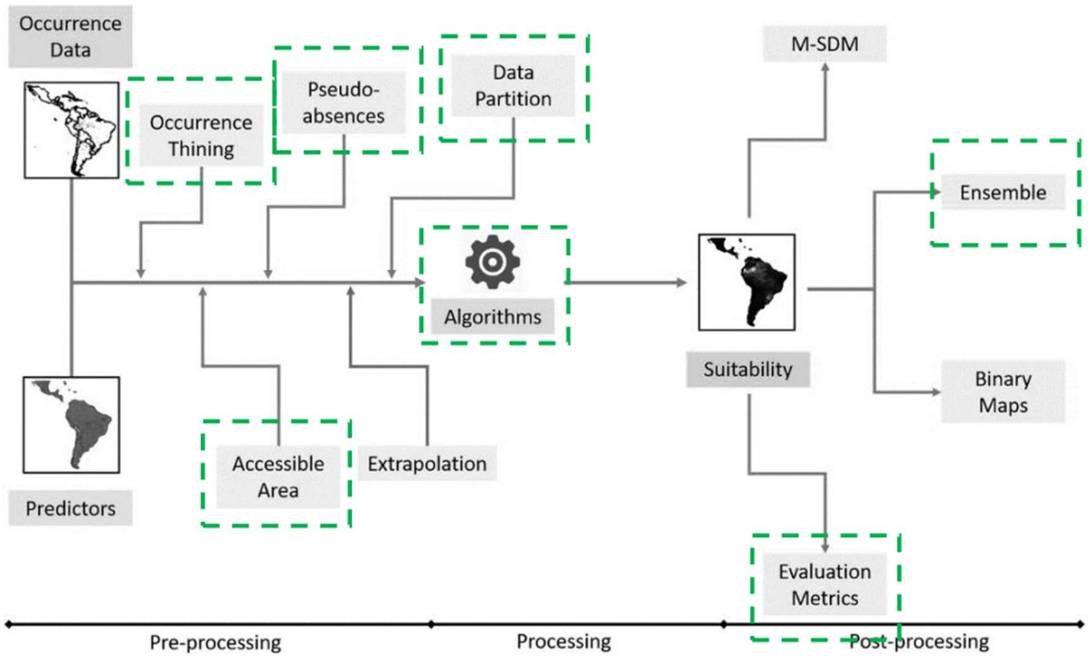

Figure 4-3. Modelling process in the ENMTML R package.
Adapted from Andrade et al. (2020). Green rectangles highlight applied settings in this study.

4.3.3 Habitat suitability index

HSI models are a quantitative approach to describe the habitat requirements of a species on a continuous scale from 0 (unsuitable) to 1 (suitable) (Wakeley, 1988). For the implemented HSI model, selected variables are aggregated using an additive priority function extended by the multiplication with eliminating factors and was based on the approach presented by (Ahmadi-Nedushan et al., 2006; Oldham et al., 2000):

$$HSI = (V_1 * V_2 * \dots * V_n)^{1/n} * E$$

Where HSI is the habitat suitability index score scaled from 0 to 1, V is an input variable scaled from 0.01 to 1, n is the total number of input variables and E represents the excluding factors, which are always determined at either 0 or 1. The excluding factors (E) were incorporated by setting several of the input variables to 0 (which always results in an HSI of

0). Specifically, excluding factors are areas covered by permanent water and imperviousness or for some species dense vegetation (e.g. forest). Furthermore, since we aim to derive habitat suitability for breeding conditions active agricultural practice is used as excluding factor because egg-pods are mechanically destroyed if the land is plowed. The final HSI model including ENM results and species-specific variables for three species of interest are described as following equations:

$$HSI_{CIT} = (ENM_{CIT} * Fallow\ fields\ and\ edges)^{1/2} * TCT * LCC * Active\ fields$$

$$HSI_{DMA} = (ENM_{DMA} * DEM * \ VegetationDensity)^{1/3} * \ TCT * LCC * Active\ fields$$

$$HSI_{DL} = (ENM_{DL} * Wadis * VegetationDensity)^{1/3} * \ TCT * LCC * Active\ fields$$

4.4 Results

4.4.1 Ecological niche and habitat suitability index for breeding sites

The results of the ENM and HSI models for the CIT, DMA and desert locust are presented in Figures 4-4 to 4-6. The breeding suitability of HSI model was calculated for the year 2019. For a better interpretation, the continuous HSI values can be ranked into discreet categories. Generally, the ranking is objective and varies from source to source (Wakeley, 1988; Walz et al., 2015). In following, we use six categories for breeding and egg-pod surviving suitability: not suitable (0), very low suitability (0.01-0.20), low suitability (0.21-0.40), medium suitability (0.41 - 0.60), high suitability (0.61-0.80) and very high suitability (0.81-1).

4.4.4.1 Italian locust

Due to climatic condition and wide ecological tolerance of the CIT, the results of ENM are quite homogenous at high suitability level (Figure 4-4). Therefore, the advantage of additional variables and analyze of actual vegetation condition and land management activity is clearly visible within the HSI output. Because CIT is known to prefer vegetation growing on fallow fields and edges of roads and fields, the high-resolution Sentinel-2 reveals higher detail and increases the breeding suitability in those areas. The results for CIT indicate that areas not suitable for breeding and egg survival are marked by the Irtysh River and flood plains characterized by dense vegetation, as well as detected active fields, which are dominant in the northern part of Pavlodar oblast. Figure 4-4 demonstrates that wide areas of suitable climate and soil conditions can be further discriminated according to actual land use and land cover conditions. In contrast to ENM, the areas with high probability for growing sagebrush/wormwood are characterized by the highest HSI, whereas ploughed land as well as wetlands are characterized by the lowest HSI. High HSI between approximately 0.65 and 0.75 indicate natural steppe.

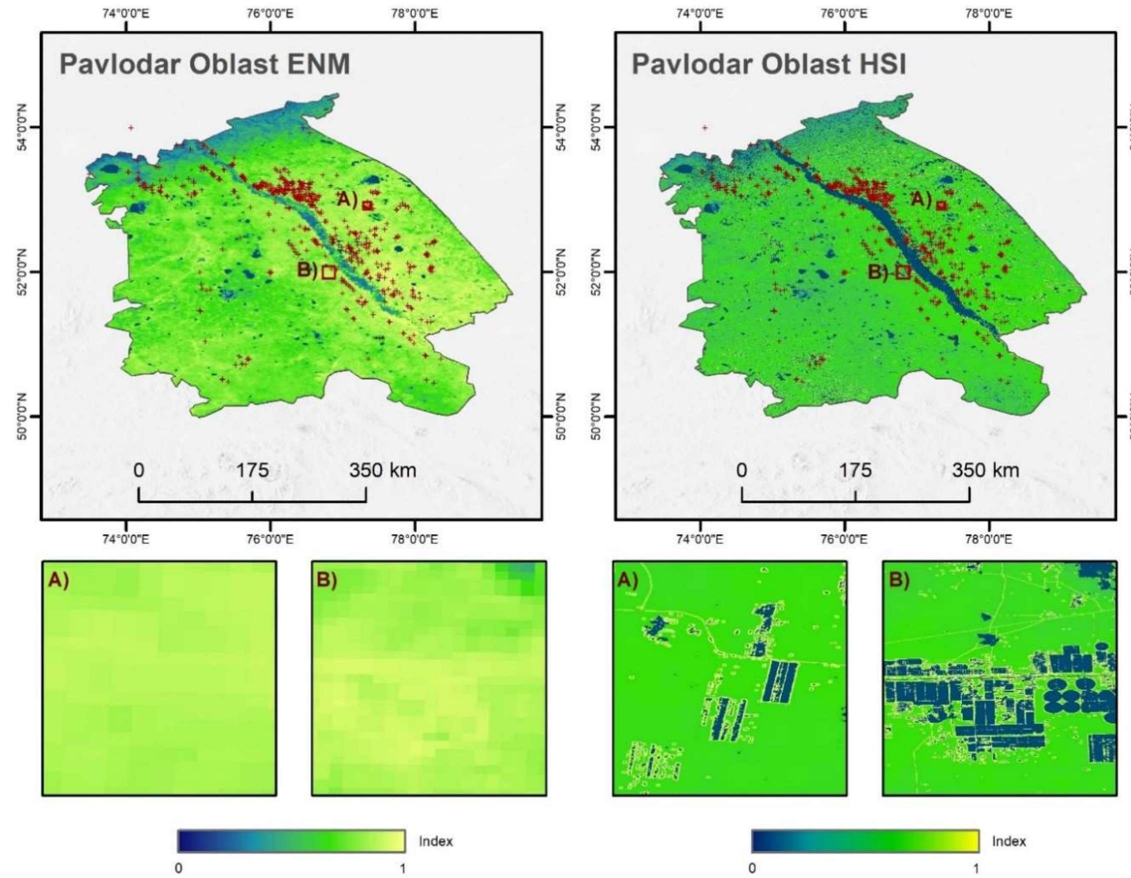

Figure 4-4. Italian locust ENM and breeding HSI for Pavlodar oblast. Red crosses: field presence locations.

4.4.4.1 Moroccan locust

The ENM and HSI results for DMA in Turkistan oblast show a clear distinction in highly unsuitable and highly suitable breeding areas (Figure 4-5). The South-West and North of the region reveal highly unsuitable breeding areas due to arid conditions and the absence of vegetation. Hilly areas with steppe vegetation show the most suitable conditions and ploughed land and bare areas are characterized by lower index. The difference between ENM and HSI can be seen West and East of Syrdarya river and Koksaray reservoir. Large areas with suitable climate, soil and elevation in the South-East become unsuitable for breeding due to active agriculture. Figure 4-5 shows the spatial upgrade between ENM and HSI within the study area. Similar to CIT in Pavlodar oblast, active land management, lakes and rivers are excluded from areas of possible breeding. Furthermore, including high-resolution DEM within HSI model accounts better for changes in elevation as DMA is sensitive to altitude and has a narrow range.

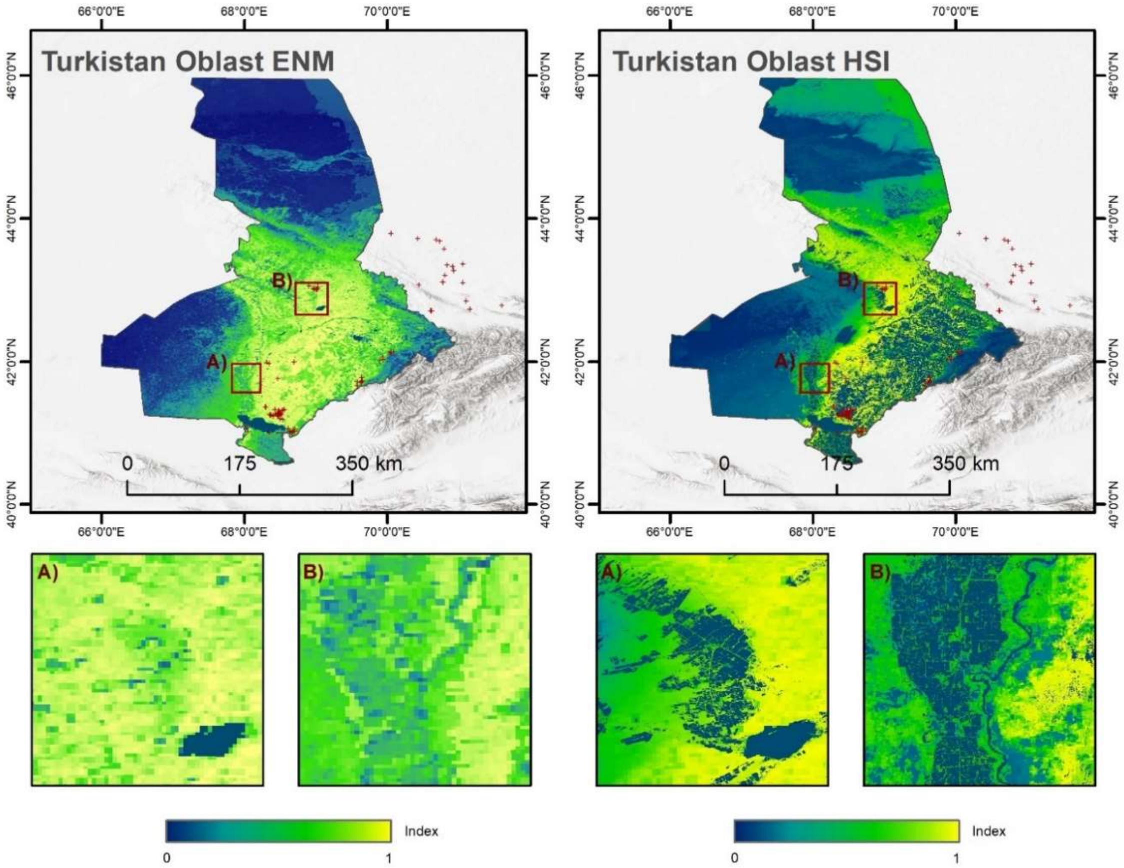

Figure 4-5. Moroccan locust ENM and breeding HSI for Turkistan oblast. Red crosses: field presence locations.

4.4.4.1 Desert locust

According to ENM output, most of the ARB is highly suitable for desert locust breeding. Only in the South-West region, a narrow strip in the West and South show unfavorable conditions. These regions receive higher precipitation and are dominated by agricultural land and forest (Figure 4-6). Higher suitability values for river reaches, wadis and sinks underline that a certain vegetation density is required for breeding and feeding. Areas with no vegetation or highly dense vegetation are characterized by a lower suitability index compared to ENM outcome. Figure 4-6 highlights this improvement and introduced heterogeneity.

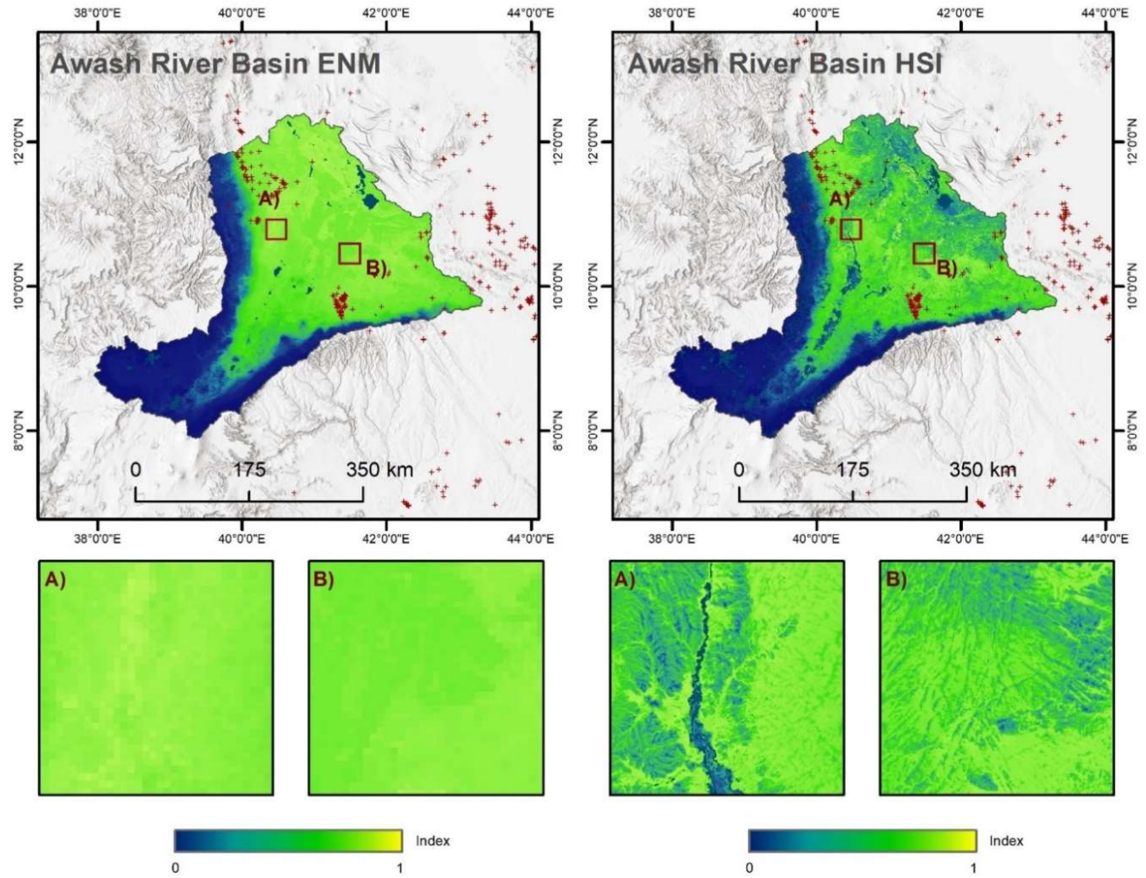

Figure 4-6. Desert locust ENM and breeding HSI for Awash river basin. Red crosses: field presence locations.

4.4.2 Validation

The main validation metric for this study was the Area Under the Curve (AUC) of the Receiver Operating Characteristic (ROC) (Fielding and Bell, 1997; Hanley and McNeil, 1982). ROC-AUC is a common assessment method for ENM and HSI results, as it does not rely on a classified, dichotomous output such as presence/non-presence (Fielding and Bell, 1997). It is a 'threshold-independent' metric and the performance of a model is estimated by creating a plot of all sensitivity values (the fraction of true positive outcomes) against the corresponding 1-specificity (the fraction of false positive outcomes) (Fielding and Bell, 1997). The AUC ranges from 0.5 to 1.0 and is often used as a single model performance measurement, because it represents the probability if a presence and an absence location are randomly modelled. The presence location will have a higher predicted value than the absence location (Raes and ter Steege, 2007). Accordingly, an AUC score of 0.5 indicates that the tested model has no predictive capabilities, while a model with a score of 1.0 has a 100% chance of predicting higher values at presence locations than at absence locations (Raes and ter Steege, 2007). However, the AUC does not indicate to which extent the predicted outcomes are higher in value than the absences. In addition, when using pseudo-absences the maximum value the AUC can reach in practice is dependent on the true distribution of the species in relation to the selected extent of the area of interest (Barbet-Massin et al., 2012; Raes and ter Steege, 2007). Therefore, it is not possible to set a fixed threshold as measure for an accurate model according to its performance as estimated through the AUC. In order to get a robust estimation of the AUC for each output of the ENM and HSI, we selected random background points as so-called pseudo-absences, while the validation occurrence locations were used as presence locations (30% split of all occurrence points within each ROI). First, for the calculation of the AUC for each study region, a pre-selection of 20,000 random background points was made (NA values excluded). In a second step, 10,000 points were selected from this pool, in order to obtain a representative distribution of non-NA background values. Finally, using the package pROC in R software, stratified bootstrapping was applied, in which a random stratified fraction of presence and background points were selected 5,000 times for the AUC calculation, after which the mean AUC value returned, as well as a 95% confidence interval (Robin et al., 2011).

Figure 4-7 presents the AUC results for CIT, DMA and desert locust based on ground truth data that was independent of the training dataset (section 3.1.5). The Y-axis represents the sensitivity, or the fraction of true positives, while the X-axis represents the specificity, or the true negative rate. It is important to note that the AUC cannot be compared across studies with different modelling extents and constraints, as the AUC is sensitive to the set-up of the sampling design (Barbet-Massin et al., 2012; Raes and ter Steege, 2007). According to computed AUC values, the prediction of the ENM model for CIT was 0.835, for DMA 0.886 and for desert locust 0.693. The reason for the lower performance within ARB can be found in the fact that the majority of the basin is quite homogenous and only a few validation occurrence points were available. The AUC result for entire East Africa and the Middle East domain was 0.951. The lower AUC for smaller ARB domain can be explained by the fact that the ARB region is more homogenous and fewer validation points were available compared (Iturbide et al., 2015). Additionally, the spread of presence points is more homogeneous within smaller AOIs compared to the spread of presence points throughout a large heterogeneous study area. Therefore, a larger extent results in a higher model accuracy (Allouche et al., 2006; Raes and ter Steege, 2007).

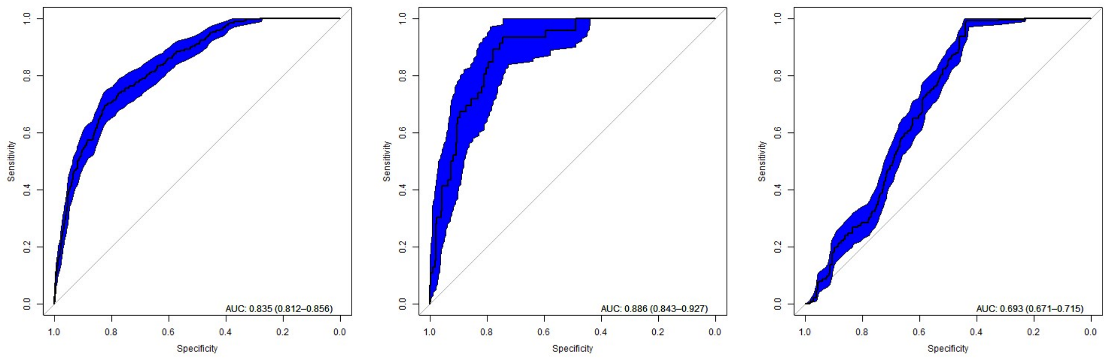

Figure 4-7. AUC for ENM results. Left) CIT in Pavlodar oblast; middle) DMA in Turkistan oblast; right) desert locust in Awash river basin.

The performance for HSI results (Figure 4-8) shows different outcomes which can be explained by the occurrence points availability and distribution as well as by the different index ranges within the areas. For CIT, the AUC of HSI output for 2019 was 0.747. Compared to coarse resolution ENM results the prediction performance of suitable breeding sites decreased by 0.088. The AUC for DMA in Turkistan was 0.850 and decreased slightly by 0.037. On the contrary, HSI results for desert locust in ARB are higher with 0.801 and increased by 0.108.

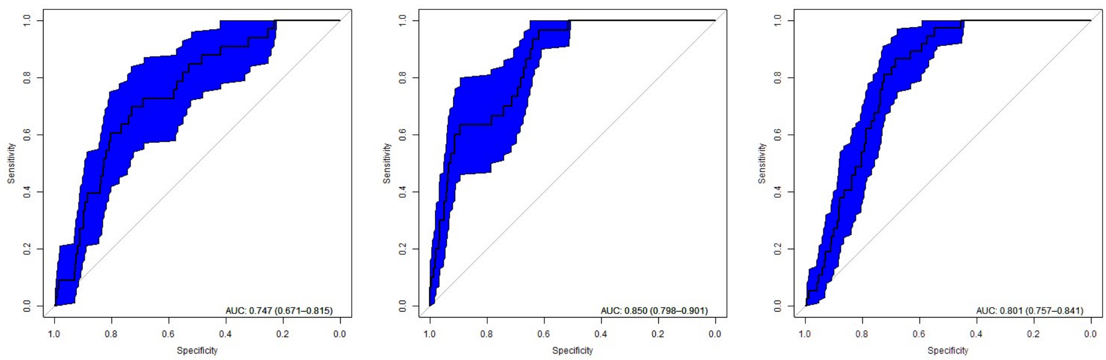

Figure 4-8. AUC for HSI results. Left) CIT in Pavlodar oblast; middle) DMA in Turkistan oblast; right) desert locust in Awash river basin.

4.5 Discussion

Ground-based surveillance demand great manpower of trained researchers to examine vast recession areas (van Huis et al., 2007). Millions of hectares have to be investigated within a narrow time window of only a few weeks (Latchininsky et al., 2016). Therefore, up-to-date habitat suitability maps with high spatial resolution and detail can contribute to improve the efficiency and focus on relevant suitable breeding areas (Cressman, 2013; Sivanpillai et al., 2009). The ENM represent the niche of species at coarse spatial resolution mirroring mainly climatic and edaphic conditions on a large scale. However, several studies have shown that land management such as grazing (Le Gall et al., 2019) or land plowing (Malakhov and Zlatanov, 2020) play essential role for locust-human linkage. Therefore, we further fused ENM results in a HSI model. This approach provides several advantages and refinements such as adding more species-related parameters (e.g. edges of fields for CIT), mirroring actual land cover by using the latest satellite data at high spatial resolution (e.g. to map abandoned fields or active cultivation) (Latchininsky, 2013). In this study, we modelled a map of breeding and egg incubation suitability for three locust species. Mapping areas suitable for egg incubation and survival at a high level of spatial detail and higher frequency can provide year-to-year alterations and an improved information for locust management. This is of special importance for species which breeding area preferences are highly dependent on land management (e.g. CIT and DMA), or sudden soil moisture and vegetation density changes (e.g. desert locust). The presented approach and derived results account for the ecological niche of the species defined by climatic and edaphic conditions but also for species-specific features such as fallow fields, field edges in the case of CIT or Wadis and terrain sinks with moisture accumulation in case of desert locust.

The high HSI AUC for DMA and desert locust shows that the presented approach is capable to perform a selective and accurate distinction in suitable and unsuitable breeding areas at a higher spatial resolution of 10 m. In the study regions for DMA and desert locust, there are limiting factors for their successful breeding such as the presence of deserts, mountains and cultivated areas. Therefore, the HSI is heterogenic, and artificially generated absence points are distributed equally over suitable and unsuitable areas. On the contrary, the situation in Pavlodar oblast is very homogenous and suitable for CIT breeding. Only wetlands, water bodies and a minor portion of regularly active fields contribute to a low HSI. Furthermore, CIT has a wide range of preferred habitats in general, while DMA has rather niche habitat preferences and its distribution is limited to particular environments (Monard et al., 2009). Therefore, given that these suitable environments can be accurately modeled, the habitats of DMA can be easier delineated from unsuitable environments than those of CIT. Artificially generated absence points are distributed across larger suitable areas and the results of AUC are less clear as random points show a higher probability in higher suitable areas. To overcome this and other restrictions related to the fact that only occurrence points are collected, ground truth absence locations are required (Fielding and Bell, 1997; Lobo et al., 2008). In general, both, selectiveness and accuracy are important for practical applications of the presented approach, because it can improve the targeting for surveys as well as for preventive locust chemical pest treatments which might be needed to limit costs and environmental damage. The accuracy depends on the species and environment of the study area. Usually, accuracy assessment for species distribution modeling leads to higher accuracies in more heterogeneous study areas, while in homogeneous areas such as Pavlodar oblast the accuracy is lower. Large study areas with easily distinguishable unsuitable habitats (e.g. high altitudes, water bodies) will lead to higher model accuracies. Nevertheless, statistical accuracy assessments of species distribution models are known to have limitations, especially when presence-only reference data is the only mean for validation (Fielding and Bell, 1997; Lobo et al., 2008). Furthermore, effects of spatial- and temporal auto-correlation likely still influenced the results, despite the split of the observational data and the spatial partitioning strategy used in the modelling process. When splitting the observational data into training and testing sets, it is assumed these are independent (Bahn and McGill, 2013). However, it is known that the surveyors often revisit sites of which it is known surveys were taken in previous years (Zaniewski et al., 2002). In addition, the surveyed areas are also often closer to roads due to their increased accessibility.

For further research, the availability of more reference data including absence points and more accurate environmental variables will reveal more opportunities to improve modeling with a more data-driven parameter tuning. A species-specific analysis and research of relevant variables and favorable conditions will improve the final results. Future investigation could adapt presented approach on larger scale and combine it with migration paths to assess the connectivity between separated habitats. Furthermore, in the context of global climate change and shifting climate zones (Mahlstein et al., 2013) as well as the alteration in land-use practices, locust habitats are also affected. This can result in more often and more intense outbreaks due to unusual rainfalls (Meynard et al., 2020; Salih et al., 2020; Stone, 2020; Tratalos et al., 2010; Zhang et al., 2019). Changing climate will also have effects on univoltine species such as CIT and DMA (one generation per year) because of the importance of winter egg diapause and weather conditions which determine the survival as well as timing of hatching. In combination with actual land management (e.g. land plowing and overgrazing) and favorable conditions suitable areas for breeding are changing throughout the time (Malakhov and Zlatanov, 2020). Therefore, monitoring efforts and international collaboration between affected countries as supported by FAO (FAO, 2021a, 2021b, 2009) have to be maintained and strengthened.

4.6 Conclusions

The goal of this research was to explore whether ecological niche modelling (ENM) and a habitat suitability index (HSI) model can be combined to refine results for actual breeding areas of three different locust pests. With the application of ENM as part of HSI, the information value based on climatic and soil preference components defining locust species' ecological niche are maintained. In addition, up to date land surface parameters, vegetation development and other species relevant environmental parameters were incorporated in the HSI model. Moreover, human interaction and actual land surface dynamics play a crucial role for locust outbreaks and influence and define suitable breeding areas. Therefore, modelling based only on climatic and edaphic variables provides only the ecological niche of a species without considering actual changes of the landscape or situation. In this study, we demonstrated a way to account for this issue by implementing different variables derived from Sentinel-2 time-series analysis, which describe the actual state of the land and in this way further narrow suitable breeding areas within an HSI model. The presented approach for mapping egg-pod incubation and breeding suitability was tested for Italian locust in Pavlodar oblast (Kazakhstan), for Moroccan locust in Turkistan oblast (Kazakhstan), and for desert locust in the Awash river basin (Ethiopia, Djibouti, Somalia). Results show high potential to enable a better prioritization and spatial focus for field monitoring to improve planning and control outbreaks without a significant loss in accuracy but an improvement in spatial detail:

- The AUC measure of the HSI maps for 2019 showed good prediction performance of 0.747 for CIT, 0.850 for DMA and 0.801 for desert locust.
- the areas of "very high breeding suitability" (0.8-1.0) and "high breeding suitability" (0.6-0.8) for Italian locust in Pavlodar oblast were 3.97% (4,970 km²) and 60.71% (75,912 km²), for Moroccan locust in Turkistan oblast 16.20% (18,765 km²) and 7.37% (8,535 km²) and for desert locust in Awash river basin 2.82% (3,045 km²) and 36.79% (39,733 km²).
- Compared to ENM alone, the area characterized by "very high breeding suitability" and "high breeding suitability" reduced by 22,1% (27,633 km²), 10,68% (12,372 km²) and 22,45% (24,246 km²) respectively.
- Therefore, presented approach could enable to account for actual land cover and consider where eggs will survive and therefore contribute to prioritize areas for locust management activities from year to year.

Historical and recent locust outbreaks around the world underline the urgent necessity for further improvement of monitoring and prediction technics. The potential of remote sensing applications has received a boost over the past few years. Improved datasets, large historical archives and cloud computing opportunities will further contribute to improve locust management to timely assess risks of infestations and take preventive and more environmentally friendly measures by treating only areas which are actually affected. In this context, it is important to consider all relevant variables and species-environment-climate-human interaction nexus to better interpret and understand data and results. The innovation of this study is a multi-scale approach which accounts not only for climatic and environmental conditions but also for current vegetation and land management situation. In this way, more explicit information can be used for risk assessment and early intervention to reduce monitoring costs, overuse of chemical insecticides (Malakhov and Zlatanov, 2020) as well as allow spatial prioritization in case of emergency or limited budgets.

4.7 References

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CHAPTER 5

5 Outbreak of Moroccan Locust in Sardinia (Italy): A Remote Sensing Perspective

Abstract

The Moroccan locust has been considered one of the most dangerous agricultural pests in the Mediterranean region. The economic importance of its outbreaks diminished during the second half of the 20th century due to a high degree of agricultural industrialization and other human-caused transformations of its habitat. Nevertheless, in Sardinia (Italy) from 2019 on, a growing invasion of this locust species is ongoing, being the worst in over three decades. Locust swarms destroyed crops and pasture lands of approximately 60,000 ha in 2022. Drought, in combination with increasing uncultivated land, contributed to forming the perfect conditions for a Moroccan locust population upsurge. The specific aim of this paper is the quantification of land cover land use (LCLU) influence with regard to the recent locust outbreak in Sardinia using remote sensing data. In particular, the role of untilled, fallow, or abandoned land in the locust population upsurge is the focus of this case study. To address this objective, LCLU was derived from Sentinel-2A/B Multispectral Instrument (MSI) data between 2017 and 2021 using time-series composites and a random forest (RF) classification model. Coordinates of infested locations, altitude, and locust development stages were collected during field observation campaigns between March and July 2022 and used in this study to assess actual and previous land cover situation of these locations. Findings show that 43% of detected locust locations were found on untilled, fallow, or uncultivated land and another 23% within a radius of 100 m to such areas. Furthermore, oviposition and breeding sites are mostly found in sparse vegetation (97%). This study demonstrates that up-to-date remote sensing data and target-oriented analyses can provide valuable information to contribute to early warning systems and decision support and thus to minimize the risk concerning this agricultural pest. This is of particular interest for all agricultural pests that are strictly related to changing human activities within transformed habitats.

5.1 Introduction

The recent outbreak of the Moroccan locust (DMA), *Dociostaurus maroccanus* (Thunberg), in Sardinia (Italy) is the worst in over 30 years (Reuters, 2022). The outbreak had already begun in 2019 and multiplied from year to year, with growing locust population and affected areas, which have increased from about 2500 ha in 2019 to 30,000 ha in 2021 and an estimated 60,000 ha in 2022 (Reuters, 2022, 2019). Historically, the Moroccan locust has been considered one of the most dangerous agricultural pests in the Mediterranean region (Latchininsky, 1998), and the first report of DMA outbreaks goes back to about 2000 years ago, when Pliny reported mandatory campaigns against locusts in Cyrene (Pantaleoni et al., 2004). In Central Asia, Caucasus, and North Africa, DMA is still a major threat for crop and pasture land, requiring regular monitoring and control activities by phytosanitary organizations. The habitat of this locust species is heavily fragmented (Malakhov and Zlatanov, 2020) and distributed from the Canary Islands in the west to Afghanistan in the east, with occurrences within the Mediterranean zone, central Europe, the Middle East, Caucasus, and Central Asia (Figure 5-1). DMA breeding sites are usually found in foothill zones and valleys approximately 400–800 m above sea level in semi-arid steppes and semi-arid deserts with a presence of abundant spring ephemeral vegetation and annual precipitation of 300–500 mm (FAO, 2021; Latchininsky, 1998). However, spring precipitation with an optimum of 100 mm is the most critical factor affecting the population dynamics. Unusual dry spring periods in consecutive years stimulate population increase and can lead to DMA outbreaks, causing economic losses and affecting rural livelihoods (Latchininsky, 1998).

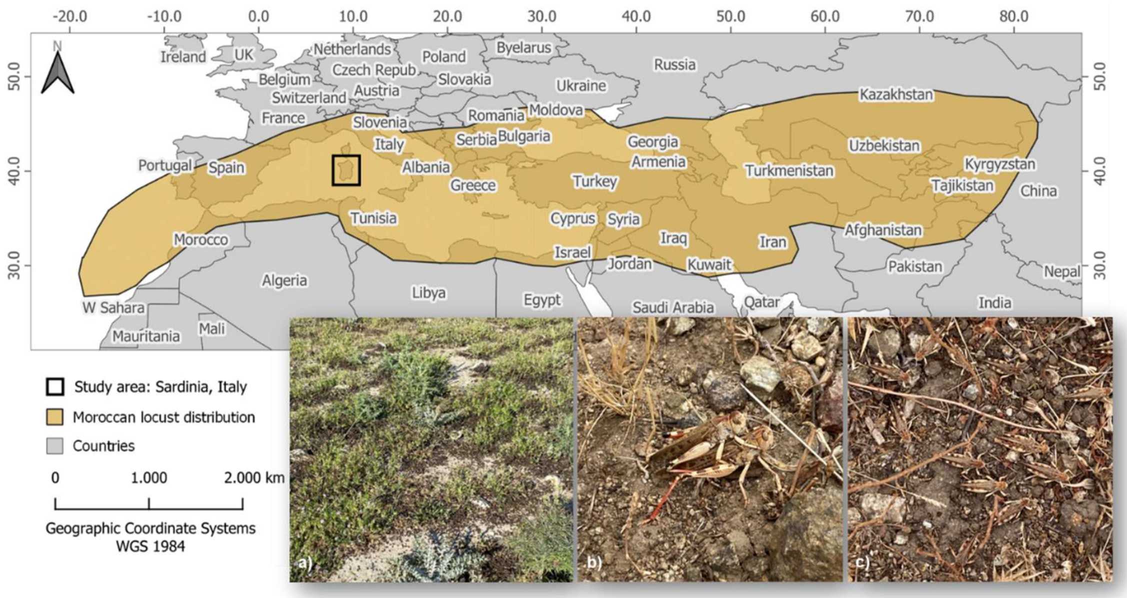

Figure 5-1. Overview of Moroccan locust distribution (adapted from FAO, 2021): (a) band of 1st and 2nd nymph stages of DMA on 26.04.2022 (40.252103 N, 8.960806 E); (b, c) mating and oviposition on 02.05.2022 (40.244172 N, 8.983378 E). Photos © Arturo Cocco.

Larger-scale damages caused by DMA in the European zone have become rare due to anthropogenic activities, such as the conversion of grassland into agricultural land. On the other hand, deforestation and overgrazing can promote the population dynamics of DMA (Latchininsky, 1998). Overall, it is well-known that land management is one of the most important driving factors for DMA population dynamics (Aragón et al., 2013; Kambulin, 2018; Latchininsky, 1998; Malakhov and Zlatanov, 2020), especially economic or political constraints, which result in increasing abandoned, fallow, and untilled areas (Latchininsky, 1998; Showler and Lecoq, 2021). Therefore, small-scale outbreaks in Spain, France, Hungary, and Italy have been documented and can occur when ecological conditions are favorable. Furthermore, climate change is expected to have significant impacts on its distribution area and population dynamics, being particularly exacerbated by several consecutive drought years (especially during spring and summer) and temperatures higher than average, as reported for Sardinia over the past years (Latchininsky, 2013; Ortu and Prota, 1989). In this context, outbreaks of locust pests in Sardinia are not uncommon and can be related to drought periods in combination with changing land management activities. For example, about 81,000 ha in 1988/1989, 75,000 ha in 1951, 1,500,000 ha in 1946, and 400,000 ha in 1933 were infested by DMA in Sardinia (Ortu and Prota, 1989).

In this context, remote sensing applications are an important asset contributing to locust preventive management strategies that includes mapping and monitoring vast areas of locust habitats (Cressman, 2013; Klein et al., 2021; Latchininsky, 2013; Zhang et al., 2019). Preventive locust management (Hunter, 2004; Magor et al., 2008; Zhang et al., 2019) is proactive and aims to detect the hazard of a locust population upsurge and control it at a smaller scale before it evolves to a large-scale plague (Latchininsky, 2013). It includes a better understanding of the species biology and ecology, more effective monitoring, early warning systems, and different control strategies. The monitoring of vast areas, which provide favorable conditions for successful breeding and potential for locust population increase, is of especially high importance for preventive locust management. This kind of geospatial risk assessment benefits highly from the availability and quality of geospatial and remote sensing datasets. Therefore, the role of remote sensing data for locust management has been growing over the past decades (Cressman, 2013; Latchininsky, 2013). The first remote sensing applications based on Landsat data were introduced by (Hielkema, 1977; Pedgley, 1974). Later, Advanced Very-High-Resolution Radiometer (AVHHR), Moderate-Resolution Imaging Spectroradiometer (MODIS), and Satellite Pour l'Observation de la Terre VEGETATION (SPOT–VGT) were applied to detect vegetation development at a higher temporal frequency, as well as Meteosat cloud imagery to estimate intense rainfall over desert locust habitats (Bryceson et al., 1993; Ceccato et al., 2006; Hielkema and Snijders, 1994; Pekel et al., 2011; Piou et al., 2013). In addition, soil moisture acquired from remote sensing data has been an important input for different habitat modelling and forecast efforts (Crooks and Cheke, 2014; Escorihuela et al., 2018; Gómez et al., 2018; Piou et al., 2019).

In this paper, the recent outbreak in Sardinia was analyzed with the application of remote sensing data to provide additional information that can contribute to support monitoring, risk assessment, and forecast efforts. The relation between recent DMA records from 2022 and abandoned/fallow or unplowed lands was quantified to demonstrate the value of up-to-date information on the actual state of the land surface derived from open-source remote sensing data. For this purpose, we applied time-series analyses of the Sentinel-2 data archives (2017–2021) with a specific focus on deriving relevant land cover and land use (LCLU) classes as well as their evolution over time.

5.2 Materials and Methods

5.2.1 Study Area

The study area is the island of Sardinia (40.000556 N, 9.115833 E), in the middle of the western Mediterranean Sea, with a total area of about 24,000 km2 (Figure 5-1). Sardinia is characterized by a typical Mediterranean climate, with mild winters and hot and dry summers. Most of the island falls into the Mediterranean pluviseasonal oceanic macrobioclimate, whereas the inner mountain areas above 800–1000 m a.s.l. are best described by temperate oceanic macrobioclimate (Canu et al., 2015; Rivas-Martínez et al., 2011). Generally, rainfalls are concentrated from October to May, whereas the dry season spans from June to September. However, the dry season can last from July to September at higher altitudes and from May to October in dryer southern areas. Mean annual precipitation is highly variable, depending on latitude, altitude, and local conditions, and ranges from 381 mm in south-eastern Sardinia to 1343 mm in north-eastern mountains (Secci et al., 2010).

5.2.2 Classification of actual state of LCLU with focus on DMA relevant land characteristics

LCLU information on the actual state of the land surface and its changes derived from satellite-based Earth observation (EO) data has played and continues to play an important role for different applications and disciplines (e.g., modelling, assessment of environmental changes, deforestation, desertification, etc.). Various global LCLU products are available at a medium spatial resolution, representing the state of the land surface at a certain time period (Bartholomé and Belward, 2005; Friedl et al., 2010; Winkler et al., 2021). The technological progress and availability of open-source satellite data at high temporal and spatial resolution has enabled improvement of LCLU accuracy as well as the level of detail by utilizing time-series analysis in combination with machine learning approaches (Pekel et al., 2016; Zanaga, et al., 2021). Nevertheless, available global products sometimes do not include the required information for specific use cases. Therefore, there are many regional LCLU products and adaptations that account for user-specific class discrimination or target explicit land cover classes of interest (Gessner et al., 2015; Klein et al., 2012; Leinenkugel et al., 2013; Pickens et al., 2020). In the context of locust outbreaks, it is well known that the current and previous land management plays an essential role (Latchininsky, 2013, 1998; Le Gall et al., 2019; Sivanpillai et al., 2009). The characterization of the land surface, specifically focusing on habitats of different locust pests, has been part of research efforts to support preventive locust management (Bryceson, 1989; de Miranda et al., 1994; Latchininsky et al., 2007; Lazar et al., 2015; Löw et al., 2016; McCulloch and Hunter, 1983; Shi et al., 2018; Zhao et al., 2020). Abandoned and fallow fields or untilled land can provide ideal breeding habitats for some locust species, thus increasing the possibility of a population upsurge and outbreaks (Latchininsky et al., 2011; Latchininsky, 2013, 1998; Monard et al., 2009; Sergeev, 2021; Sivanpillai et al., 2009). On the contrary, regular mechanical treatment of fields and pasture (plowing) usually destroys locust eggs and hence contributes to population decrease (Sergeev et al., 2022).

To quantify the relation between the current DMA outbreak in Sardinia and land management and abandonment, we derive LCLU information with specific requirements. First, the required LCLU has to include the class “abandoned land, fallow fields, or not tilled land” to provide information on whether land has previously been plowed or not. This requirement can be fulfilled by applying time-series analyses of satellite data archives. Due to the unique phenology of agricultural land (plow, sow, growing, harvest), it is possible to distinguish between cropland and natural rangeland vegetation (Estel et al., 2015; Orynbaikyzy et al., 2020; Prishchepov et al., 2013; Verbesselt et al., 2010; Zeng et al., 2020). Using such seasonal characteristics and comparing years of interest with each other, the evolution of agricultural land or fallow fields can be derived. Furthermore, it is also very important to identify the time since the land was last plowed. Therefore, the second requirement is that the derived “abandoned land, fallow fields, or not tilled land” class should contain a “time-stamp” indicating when it was last tilled. This information can provide an indication of the vegetation composition and succession of the area (Benjamin et al., 2005), which is also important for locust habitats. Finally, the actual state of abandoned/fallow/untilled areas is also of high interest to assess whether it fulfills the habitat requirements of the locust species. Ephemeral grasslands with patches of bare soil are ideal for the egg laying and breeding of DMA (Latchininsky, 1998). On the other hand, dense vegetation (e.g., forest) or saline soils are avoided. Therefore, the third requirement is to provide the up-to-date land cover state of formerly tilled land to assess where DMA has laid eggs over the past upsurge years.

Figure 5-2 illustrates the entire workflow to achieve the discussed requirements. Since recent mapping efforts, such as the ESA WorldCover (Zanaga, et al., 2021), already provide a high level of detail and accuracy at a reasonable spatial resolution, we implement certain land cover classes that are not the focus of the presented use case (settlements, wetlands) to avoid confusion and improve the accuracy of the classes of interest. For detection of all other land cover classes and their evolution, training points were collected according to the class specifications. The assignment of sampling points was based on the visual interpretation from very high-resolution data within Google Earth Engine (GEE) in combination with time-series composites of vegetative seasons. To ensure temporal transferability of the classification model, we collected training samples for a meteorologically dry year (2017), a wet year (2018), and a normal year (2021) (ARPAS, 2021). In total, 200 training points were collected per class and year. As depicted in Figure 5-2, training points were gathered for the classes water, cropland, sparse vegetation, dense vegetation, and bare soil. The sampling database was partly used to train (75%) the random forest model that was applied on different time-steps as well as for the validation of the results (25%). Moreover, the annual Sentinel-2 composites between 2017 and 2021 were calculated on GEE platform. To mask clouds, the cloud probability data on GEE was applied. Next, the variance and 95th percentile of the normalized difference vegetation index (NDVI) was calculated at an annual scale covering the months from March to November. The annual image composites were calculated using the median value of a year, and afterwards, the median of the additional spectral indices NDVI, modified normalized difference water index (MNDWI), normalized difference built-up index (NDBI), and salinity index (SI) were derived. Seasonal images for spring, summer, and autumn were included as additional features as well. The seasonal features include the median values and the variance and 95th percentile of the NDVI.

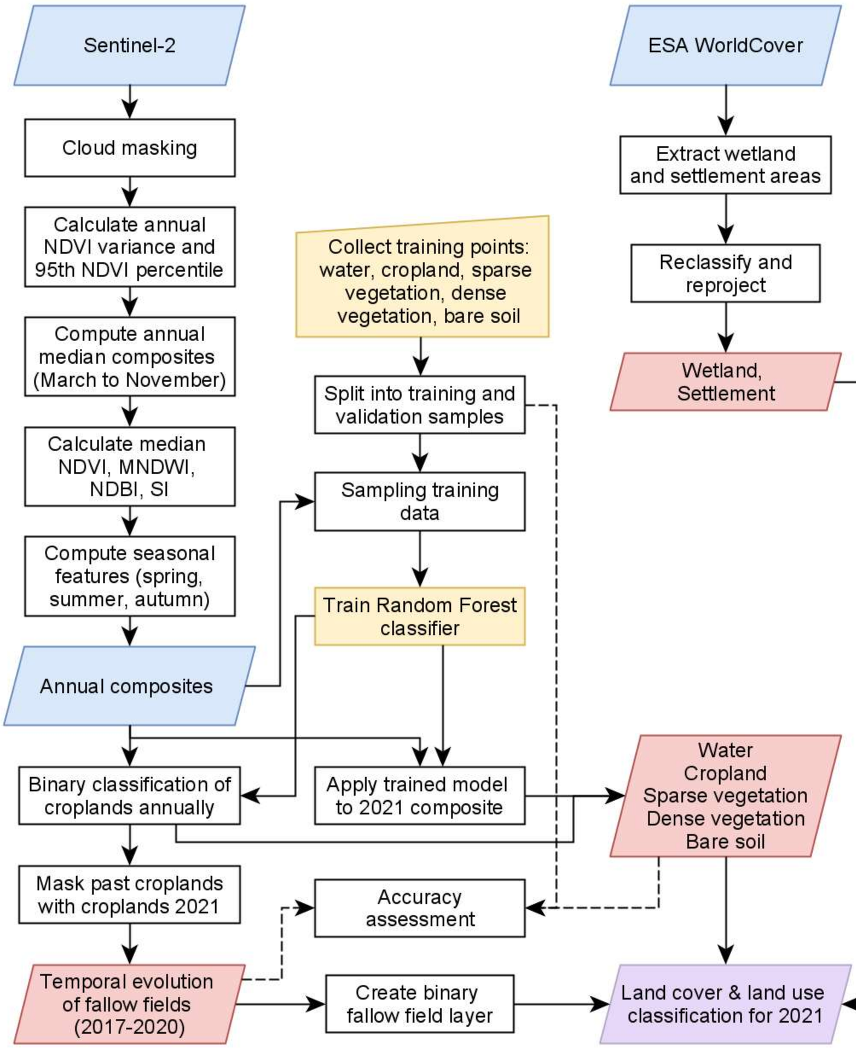

Figure 5-2. Workflow for regional land cover classification with regards to land cover classes of interest and specification to detected abandoned land.

Based on all features and training points, a random forest (RF) classification model was trained for the year 2021. Here, RF (Breiman, 2001) was selected as classifier as it is widely applied for land cover classifications and reported to be one the superior machine learning algorithms (Dirscherl et al., 2020; Dubertret et al., 2022; Phan et al., 2020). Next, an additional classification model was trained to retrieve binary cropland layers for the annual composites between 2017 and 2021. Finally, based on these annual layers, spatio-temporal information on the development of fallow fields was extracted based on an intersection with the cropland class in 2021. This spatio-temporal layer includes the information of which year an area was plowed for the last time.

As illustrated in Figure 5-2, an accuracy assessment was conducted by means of the collected point samples. To this aim, a confusion matrix was calculated for the classes water, sparse vegetation, dense vegetation, and bare soil. Due to the binary classification of croplands, this class was validated separately. In order to assess the accuracy of the classifications, the overall accuracy and Cohen's kappa coefficient (Cohen, 1960) were calculated based on the confusion matrix.

Apart from the described process and used datasets for classification, 15-day NDVI median composites were calculated for the period between March and July 2022 to analyze the relation between temporal vegetation development and different locust nymphs' states. Furthermore, we used a 30 m spatial resolution digital elevation model dataset (DEM GLO-30) for additional interpretation of the role of elevation for breeding conditions within the study region (Copernicus, 2022).

5.2.3 Moroccan locust records locations

DMA infestation in 2022 included two separate areas in central Sardinia and spanned overall from north (40,4821623 N, 9,1214687 E) to south (40,1067563 N, 8,9625105 E) and from east (40,2966785 N, 9,181988 E) to west (40,2488991 N, 8,8236914 E). The two infested areas extended for about 100,000 ha and 12,000 ha, respectively. Within the largest area, an abandoned industrial area and a photovoltaic solar power plant rise over about 400 ha. The majority of record locations were distributed within a plain area with small hills on hard soil (untilled) and exposed south, being an area well known to have been a hotspot and ideal habitat of previous DMA outbreaks in Sardinia (Molinu et al., 2004; Ortu and Prota, 1989). The University of Sassari (Italy) together with LAORE (Regional Agency for Agriculture Development) have been closely observing the ongoing outbreak and collecting different information on the DMA infestation, including coordinates of infested locations, altitude, and DMA developmental stage. For locust management purposes and preventive control measurements, it is important to detect locations where locust has hatched successfully and is present at high density. A total of 814 locations with different DMA development stages were recorded between March and July 2022 and classified into the following categories: young nymphs (1st–2nd instars) (113 locations), mature nymphs (3rd–5th instars) (435 locations), feeding/moving adults (181 locations), and breeding sites (85 locations). Infested locations were detected by field surveys carried out by LAORE extension agents and researchers of the University of Sassari in the areas infested by DMA in the previous year. The DMA developmental stage was determined by visual observations of specimens by a sweep net. Locations were defined as breeding sites when adults were observed breeding or female's oviposition.

Sites characterized by young nymph bands can be also considered as locations where breeding was successful in the previous year because young locust insects cannot move far at this stage. Nevertheless, locust nymphs at early-stage development are capable of moving up to 100 m or even 150 m per day depending on species, weather conditions, and green vegetation availability (FAO, 2021; Symmons and Cressman, 2001). In order to account for possible daily displacement from original breeding locations and uncertainties, a 100 m buffer was created around young nymph and breeding record locations.

5.2.4 Combination of nymph locations with data from remote sensing

The geographic coordinates and dates of detected DMA locations from 2022 were utilized for further analysis in terms of land cover situation and ongoing DMA outbreak. The data was intersected with the results of LCLU mapping results from 2021 as well as with 15-day composites of NDVI. In this way, this analysis provides a quantitative and qualitative assessment of DMA locations with regard to actual land surface conditions, the vegetation development during instar stages, and possible previous land management activities. Finally, differences in the distribution of DMA development stages among LCLU were evaluated using a $\chi 2$ test for independence ($p < 0.05$), followed by the calculation of Pearson's standardized residuals.

5.3 Results

5.3.1 Relation of DMA locations with previous and actual land cover

Out of 814 detected DMA records from 2022, 43% (347) were found on land classified as "abandoned, fallow, or not tilled" in the year 2021 (Figure 5-3). A further 29% (236) were located on sparse vegetation/grassland. A total of 5% were located in other classes (2, 16, and 26 in the dense vegetation, built-up, or bare soil land cover classes, respectively). Finally, 23% (187) were found on land classified as cropland. At this point, it is important to consider two facts. First, classification from remote sensing comes along with some uncertainty and misclassifications (compare Section 3.3), which depend mainly on the accuracy and definition of the training data, input data quality (e.g., data gaps, clouds, viewing angles), input data characteristics (e.g., temporal, spatial, and spectral resolution), and applied methodology. Secondly, the detection of nymph locations also differs from the actual origin where egg pods where laid and nymphs actually hatched (compare Section 2.2). Both factors are of relevance for the interpretation of derived information from Sentinel-2 data at a spatial resolution of 10 m. Therefore, we also considered the buffered area to examine whether abandoned/fallow land is found in the direct vicinity of reported locations. This assessment shows that 23% of breeding spots located in classified active agriculture are within 100 m of untilled land. Therefore, two conclusions can be made. Either locust nymphs have dislocated to cropland areas and were detected there by the ground teams, or cropland was misclassified, because mechanical plowing of soil would usually lead to the destruction of eggs.

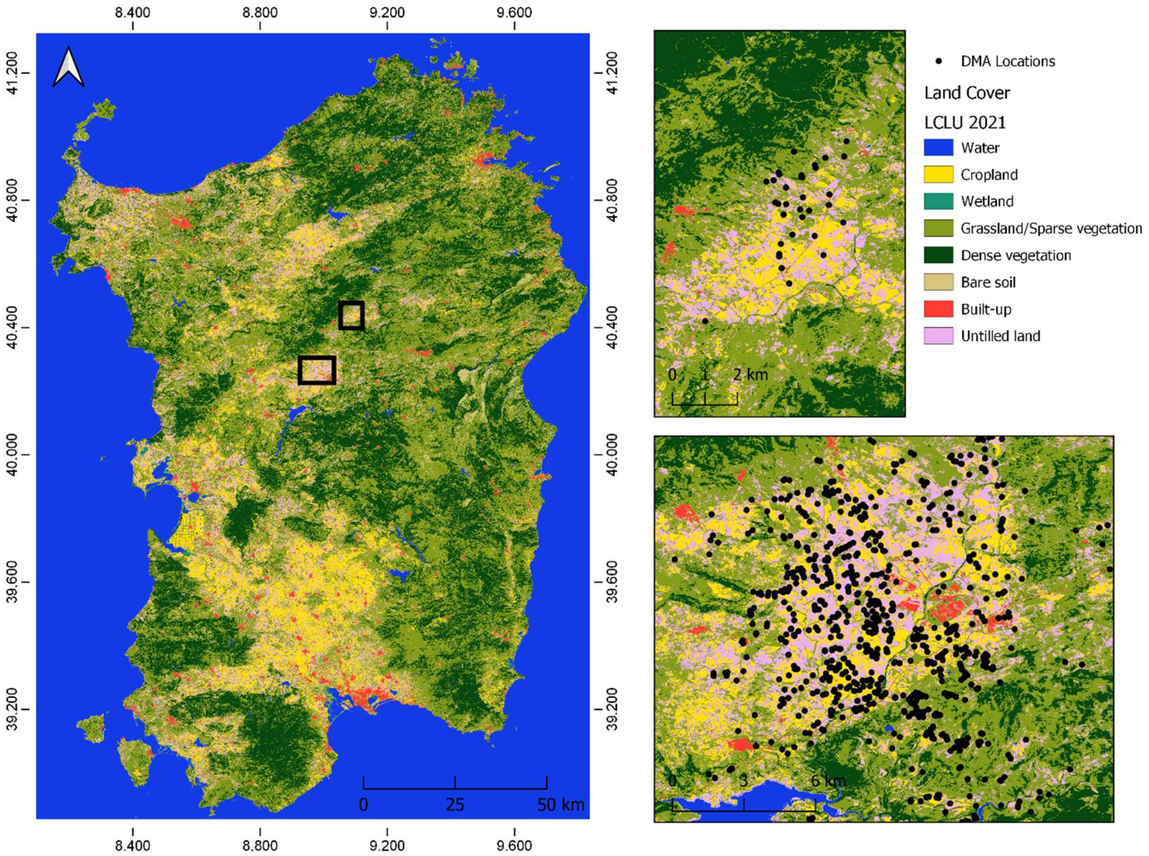

Figure 5-3. Land cover land use classification for 2021. Zoom areas for region of interest with majority of detected DMA locations.

Statistical differences in the distribution of DMA development stages among LCLU were found ($\chi 2 = 43.46$, df = 12, $p < 0.05$). In particular, the occurrence of younger DMA nymphs was significantly higher than expected in locations identified as untilled lands. Moreover, the occurrence of feeding/moving adults was significantly higher than expected in areas with sparse vegetation and grassland and lower than expected in untilled lands (Table 5-1).

A more detailed consideration and distribution of locations with regard to different detected DMA life stages is provided in Table 5-1. In the following, we assume that young nymphs of the first and second stages are found close to their breeding sites and consider them as one group. Therefore, the total of 113 (young instar) and 85 (oviposition) represent precise locations where egg pods were actually laid. Out of these locations, 73% (144) were located within the class “sparse vegetation/grassland”. In addition, 53% (104) of these breeding locations were also classified as formerly active agriculture or pasture land (Figure 5-4). A total of 48 records (24% out of the total breeding sites) were found on active agriculture land. Only four records were found on bare soil, and two on other land cover classes (3% in total).

The older instar stages and adults, which have a higher capacity to move and have had a longer time period to dislocate from their origin of breeding, show only a slightly different picture. Out of a total of 616 locations, 71% (437) were located within the class sparse vegetation/grassland, whereas 39% (241) were also classified as formerly active agriculture or pasture land. Another 23% (139) of the total older instar stages and adult records were found on active agriculture land.

Besides the identification of land that has been used for active agriculture, we also derived the time when this land was last tilled or actively used. This evolution of abandoned, fallow, or not tilled/plowed land is presented in Figures 5-4 and 5-5 and Table 5-1. The majority (88%, 307) of the 347 positions are found on land that has been fallow or untilled since 2020. This suggests that DMA has found perfect conditions on this relatively "young" untilled land, which is in line with observations and documentations of previous DMA upsurges (Latchininsky, 1998; Monard et al., 2009). Compared to the years 2017, 2018, 2019, and 2020, the year 2021 is characterized by less agricultural activity (Figure 5-4). Among all locations that were found to be fallow or untilled since 2020, 97% (338) were classified as sparse vegetation/grassland in 2021 (Figure 5-6, Table 5-1).

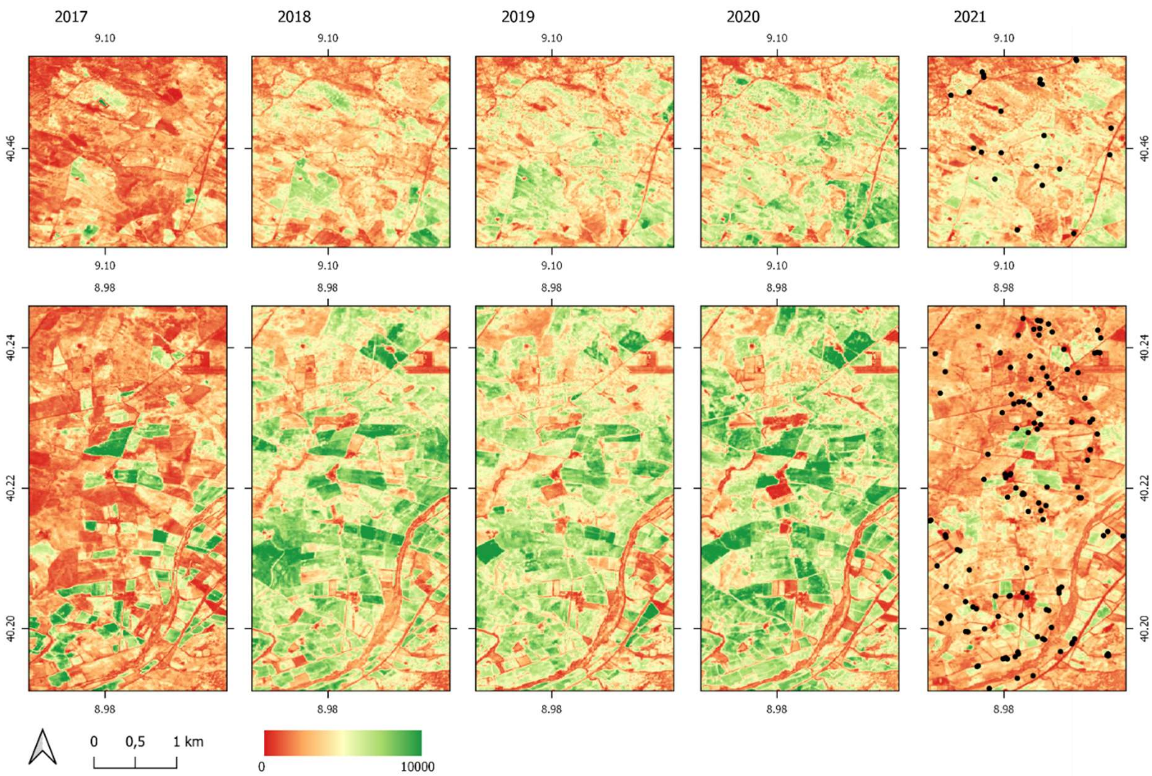

Figure 5-4. NDVI variance for vegetative period (Mar–Nov) for 2017–2021 as an indicator for agricultural activities. Zoom in to both regions with high density of DMA locations in 2022 (compare 2.2). Black dots = recorded DMA locations in 2022.

Table 5-1. Distribution of DMA locations among different classes of 2021 and untilled land evolution[1]. Pearson standardized residuals measuring the deviation from expected values are reported in brackets (+ = positive deviation; − = negative deviation).

	LCLU 2021					Untilled Since				Untilled LC 2021	
DMA Stage	C	S	B	O	U	2017	2018	2019	2020	S	B
N1-N2 (113)	23	25	0	1	64 (+)	1	2	0	61	62	2
N3+ (435)	103	119	21	9	183	5	20	1	157	178	5
Feeding/moving adults (181)	36	77 (+)	3	7	58 (-)	1	7	3	47	56	2
Oviposition (85)	25	15	2	1	42	0	0	0	42	42	0
Total (814)	187	236	26	18	347	7	29	4	307	338	9

[1]First and second nymph stages (N1-N2), third or older nymph stages (N3+), cropland (C), sparse vegetation and grassland (S), bare soil (B), other classes (O), untilled land (U).

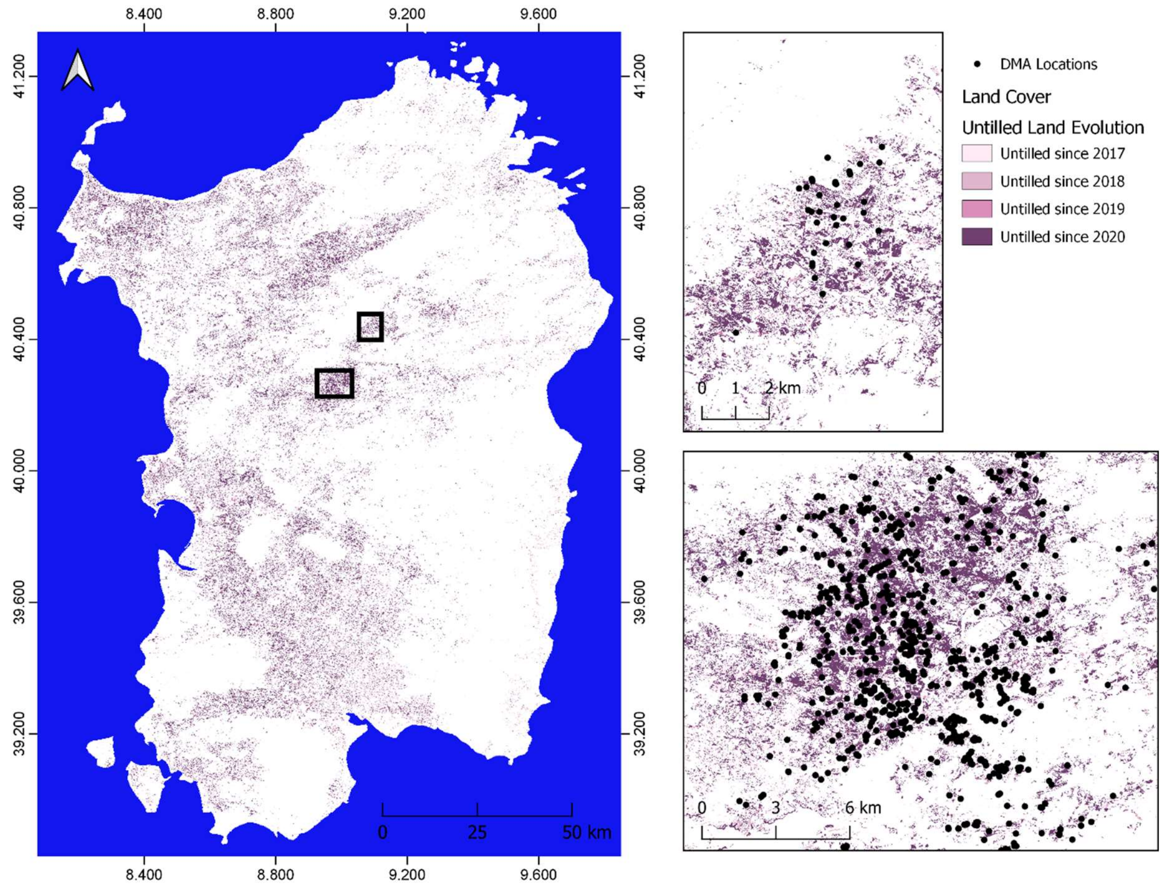

Figure 5-5. Abandoned land evolution 2017-2020. Zoom areas for region of interest with majority of detected DMA locations.

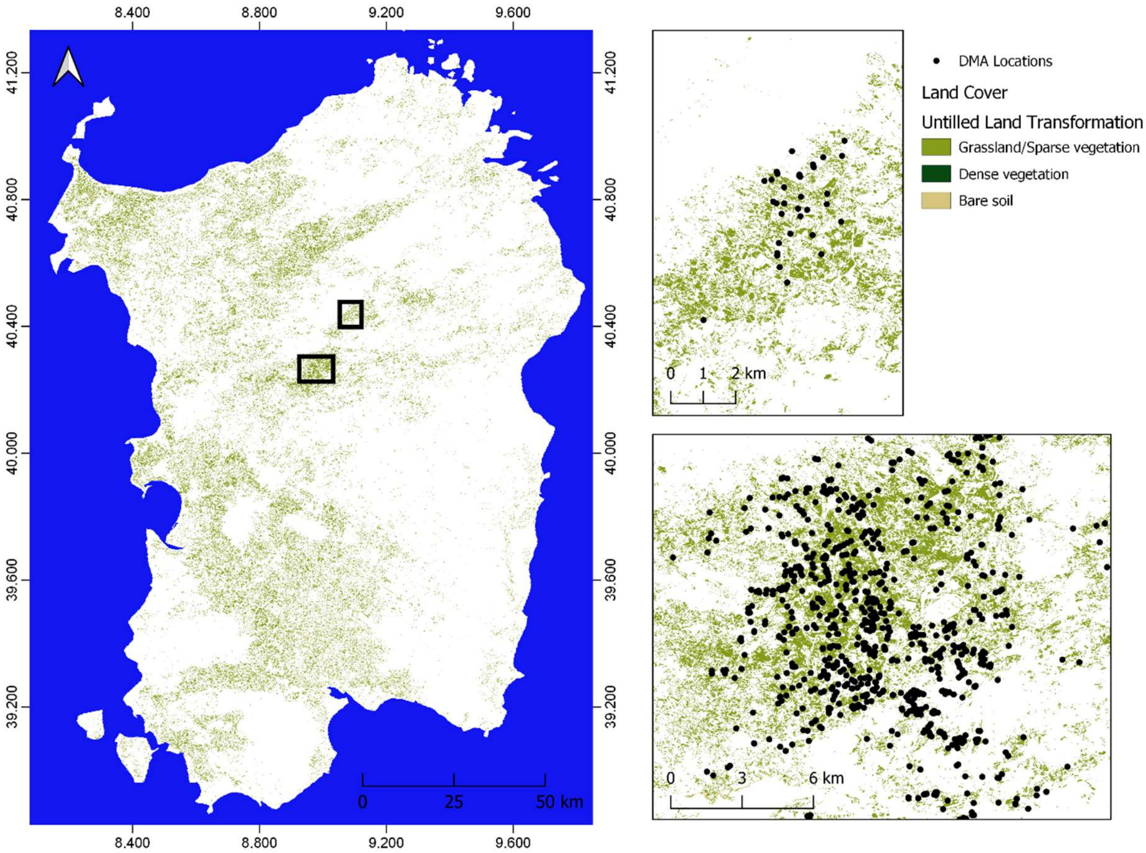

Figure 5-6. Abandoned land transformation and state in 2021. Zoom areas for region of interest with majority of detected DMA locations.

5.3.2 Accuracy assessment

The generated LULC map for the year 2021 resulted in an overall accuracy of 96.4% and a kappa coefficient of 0.951. As listed in Table 5-2, the binary cropland layers have an overall accuracy and kappa coefficient of 96.75% and 0.898 for 2021, 92.37% and 0.747 for 2018, and 96.34% and 0.867 for 2017.

Table 5-2. Results of the accuracy assessment for the binary cropland classification in 2017, 2018, and 2021[1].

Classes	Cropland				Non-cropland				Both	
Accuracy Measure	EO [%]	UA [%]	EC [%]	PA [%]	EO [%]	UA [%]	EC [%]	PA [%]	OA [%]	K
2017	14.29	85.71	7.69	92.31	1.47	98.53	2.90	97.10	96.34	0.867
2018	34.55	65.45	0.00	100.00	0.00	100.00	8.92	91.08	92.37	0.747
2021	15.09	84.91	0.00	100.00	0.00	100.00	3.98	96.02	96.75	0.898
Average	21.31	78.69	2.56	97.44	0.49	99.51	5.23	94.73	95.15	0.837

[1] For each year the accuracy measure Error of Omission (EO), User's Accuracy (UA), Error of Commission (EC), Producer's Accuracy (PA), Overall Accuracy (OA), and Kappa coefficient (K) is provided.

5.3.3 Relationship of DMA locations with vegetation development and elevation

Besides the outcome of actual land cover as a discrete classification, remote sensing data can provide more detailed temporal information that is of higher relevance to assessing and understanding locust outbreaks and life cycles. In general, locust development and population dynamics depend highly on vegetation cover and its development over time (Cisse et al., 2013; Despland, 2003; Deveson, 2013; Pekel et al., 2011; Piou et al., 2013; Renier et al., 2015; Waldner et al., 2015). Therefore, we also performed NDVI of biweekly and monthly composites to present the relation in this regard for the outbreak of 2022.

The results demonstrated a clear pattern between NDVI development and detected DMA life stages (Figure 5-7). The young nymphs (N1-N2) were detected in April within the peak of the vegetative period. In May and June, when older nymph stages (N3+) and adults were detected, the NDVI around these locations has already decreased. Oviposition took place in July and June, when vegetation subsidence has already occurred. In general, it seems that there is no implication that older nymphs or mature insects were moving towards greener areas. However, it should be considered that untilled, fallow, and abandoned land, as well as pasture and grassland, are not irrigated, and plants tend to dry out from the end of May onward due to rain scarcity and high temperature.

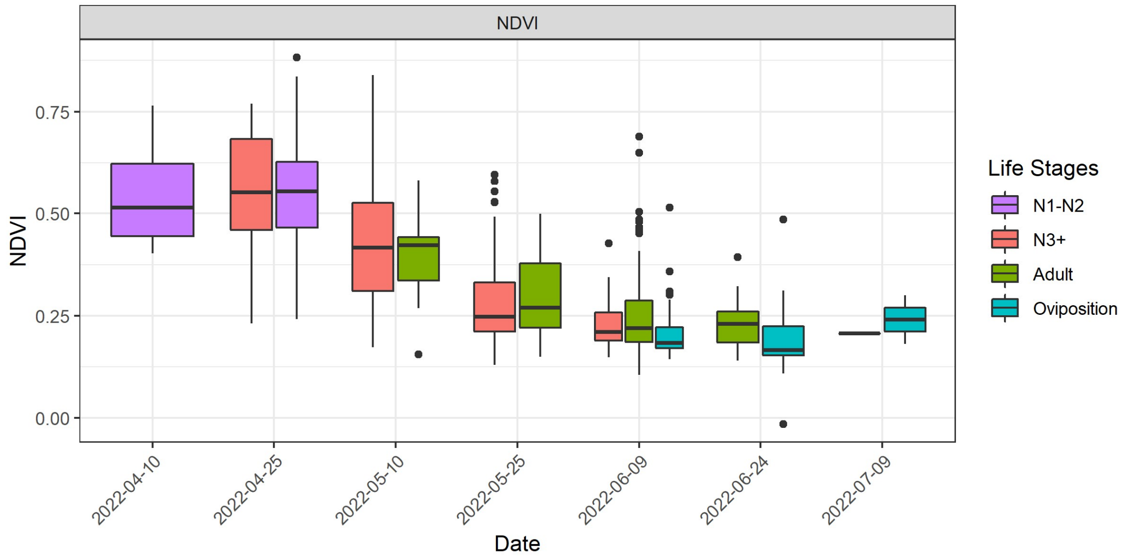

Figure 5-7. Bi-weekly NDVI development for different stages of detected DMA locations between April and July 2022.

Additionally, we also extracted the elevation from a DEM to provide any indication related to relief as described by Ortu and Prota (1989) (Figures 5-8 and 5-9). The relation between elevation and detected locations for different Moroccan locust life stages shows a slight increase in height with proceeding time until the end of May. DMA was reported between 137 and 680 m above sea level (a.s.l.), with the majority of records (647 records, 79%) between 137 and 250 m, although preferred habitats are restricted to foothills and valleys at a range of 400 and 1200 m a.s.l. (Latchininsky, 1998; Zhang et al., 2019). This difference could be due to peculiar microclimatic conditions characterized by wide temperature excursions in spring that could promote optimal DMA development at lower altitudes.

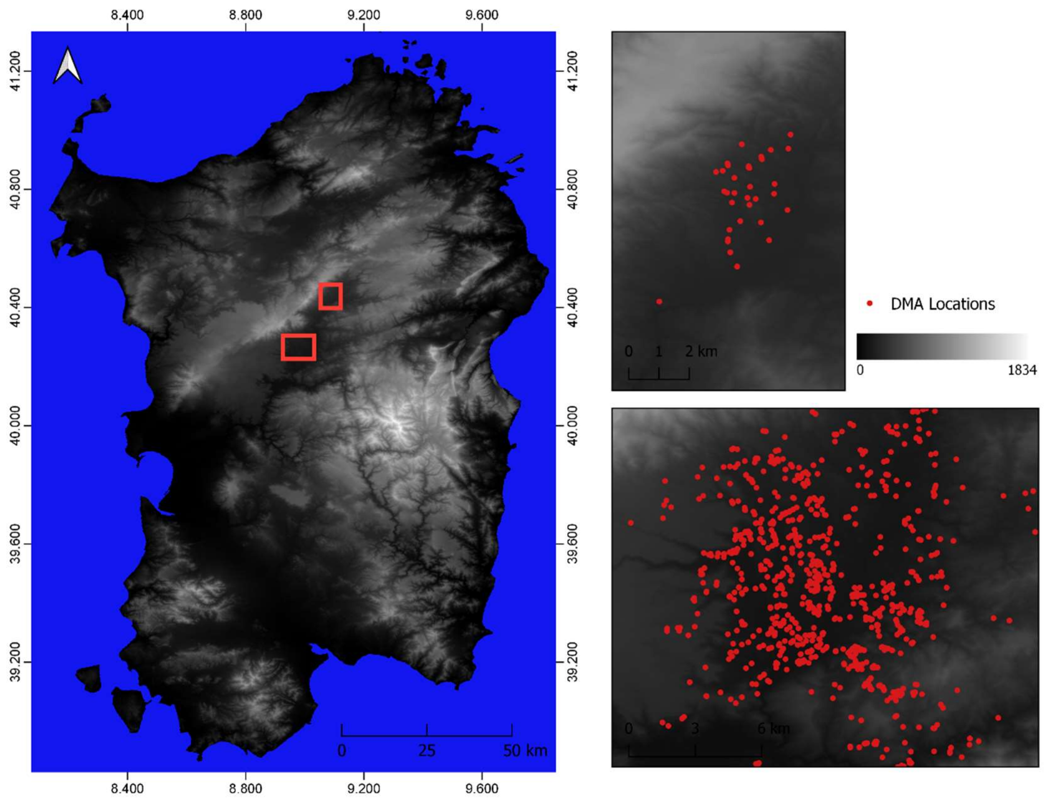

Figure 5-8. DEM at 30 m spatial resolution (source: Copernicus-DEM derived from Tandem-X DEM). Zoom areas for region of interest with majority of detected DMA locations.

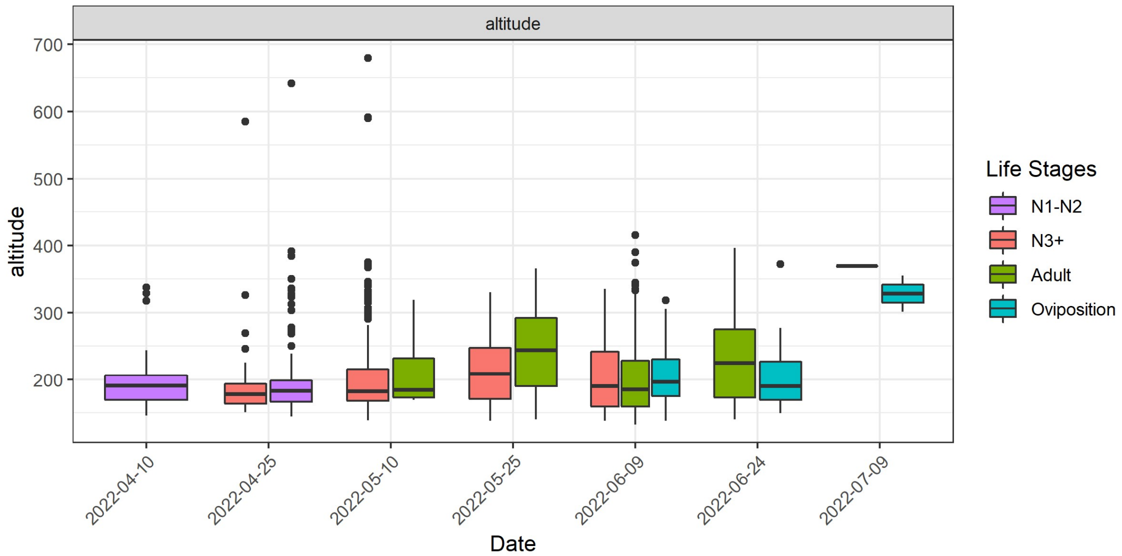

Figure 5-9. Relation between elevation and time for different stages of detected DMA locations between April and July 2022.

5.4 Discussion

Land cover classification and potential habitat mapping in the context of locust outbreaks have been mainly performed based on Landsat and MODIS datasets for the migratory locust (*Locusta migratoria*, LMI), whose habitats are associated with reed vegetation in temporarily inundated areas along rivers and within deltas (Geng et al., 2020; Latchininsky et al., 2007; Löw et al., 2016; Shi et al., 2018; Sivanpillai and Latchininsky, 2007; Zhao et al., 2020). Land cover transformation due to overgrazing, deforestation, flood plain drainage or agriculture abandonment plays an important role for other locust pests, such as Moroccan locust (*Dociostaurus maroccanus*, DMA) and Italian locust (*Calliptamus italicus*, CIT) (FAO, 2021; Latchininsky, 1998). Approaches utilizing modern open-source remote sensing datasets (e.g., Sentinel-1, Sentinel-2) with a specific focus on locust requirements concerning actual land cover situation and its evolution still have to be developed and optimized for different species. In this study, we demonstrated that specific land cover classification and its consideration over time can provide valuable information as to where potential areas are experiencing land cover transformation and, in this way, becoming favorable for further locust breeding. Sentinel-2A/B Multispectral Instrument (MSI) datasets provide an ideal foundation for monitoring potential territories and detecting habitat transitions. The recent DMA outbreak in Sardinia, as well as local outbreaks in other countries, emphasize that DMA is a serious agricultural pest in places where ecological conditions and human activities are changing. Concerning the European part of the DMA habitat, Latchininsky (1998) reported that the economic importance of its outbreaks was vanishing during the second half of 20th century due to the high degree of agricultural industrialization and other human-caused habitat transformations. However, due to climate change causing recurrent drought periods, and in combination with less anthropogenic pressure(Latchininsky, 1998), DMA outbreaks might become more serious again. Since Moroccan locust and other locust species outbreaks are also closely related to human activities, it has to be kept in mind that locust outbreaks might become a major threat in Europe and elsewhere again once conditions change (Latchininsky, 1998; Lecoq and Cease, 2022; Showler and Lecoq, 2021). Therefore, we consider the presented approach using Sentinel-2 data and adjustments on land cover classification and temporal analyses for specific locust pest to have a high potential to support future risk assessment and preventive locust management. First, this is because it can be done independently and comparably quickly, and in an economical way. Secondly, remote sensing provides information on a large scale and thus also for areas that have not suffered any locust outbreaks recently but might become important due to climate change, land management alterations caused by institutional changes, political programs, crises, and wars (Kraemer et al., 2015; Prishchepov et al., 2012; Winkler et al., 2021). With regard to food security, it is crucial to monitor land cover and other relevant parameters more closely for the specific requirements of different agricultural pests.

Analysis of the distribution of different DMA development stages among different land uses showed that younger nymphs were mainly located in untilled lands (Table 5-1). Since locations where young nymph bands occurred were considered as sites in which breeding was successful in the previous year, our results confirmed that DMA breeding sites are mainly represented by abandoned and/or untilled lands, where the most favorable conditions for egg survival and development occur (Ortu and Prota, 1989). On the other hand, the occurrence of adults was recorded more often in areas with sparse vegetation and grassland, whereas the occurrence of adults was significantly lower in untilled lands (Table 5-1). In fact, adults feed more than those in the juvenile stages because they need to accumulate energy for flight and dispersion, so they move onto vegetation-covered land. However, these results should be interpreted with caution due to potential spatial autocorrelation among DMA records. Although younger nymphs have a low dispersion ability, so that their distribution over the area is more likely due to small-scale ecological processes, adults have a high dispersion ability. This makes it possible that locations where adults occurred were not spatially independent from each other (Legendre, 1993). Additional field data collection (including absence locations) and availability over several years would enable further analyses of the spatio-temporal dynamics of locust populations and also reduce possible impacts of spatial autocorrelation in the evaluation of the relation between locust locations and land surface conditions.

In the future, detailed analyses of different relief variables and more detailed plant and vegetation type discrimination derived from remote sensing data might contribute to additional improvements in terms of remote-sensing-based monitoring of locust population dynamics. Furthermore, post-locust-infestation damage assessment and the question of whether vegetation and crop loss can be quantified from remote sensing data can be explored. To address this objective, field data with specific information on ground detected vegetation damage and timely coupled satellite data at higher spatial, temporal, and spectral resolution are required. Previous investigations utilizing MODIS data showed that optical moderate-resolution sensors might be insufficient to detect vegetation damage related to locust infestation (Adams et al., 2021; Weiss, 2016).

5.5 Conclusions

In this study, we quantified the relation between detected DMA locations from 2022 field campaigns with actual land cover situation and development over previous years. As stated by Ortu and Prota (1989), DMA oviposition occurs mostly in compact (untilled) soil exposed to the south. The relation between recent DMA outbreak and land surface under human influence is as follows:

- 43% were located on land that was previously used for agriculture purposes (fallow or previously tilled land);
- 23% were located on cropland within a radius of 100 m to abandoned, fallow, or untilled land, due to possible displacement after hatching as well as possible inaccuracy of land cover classification;
- The majority of locations detected on abandoned, fallow, or untilled land were occupied by active agriculture until 2020, which indicates that DMA occupied this territory immediately;
- Considering the transformation of abandoned, fallow, or untilled land, the majority of locations are found on the sparse vegetation/grassland land cover class (97%).

Moreover, we quantified the hatching time and DMA life cycle development according to vegetation development and elevation. Based on those analyses, the following conclusions can be made:

- Young nymphs were detected in April within the peak of the vegetative period;
- Older nymphs and adults were found in areas with significantly decreased vegetation greenness;
- In terms of altitude, the majority (79%) of DMA locations were found between 137 and 250 m a.s.l.

This study demonstrates that valuable up-to-date information from remote sensing data can be derived for DMA upsurges. Such information can contribute to early warning systems and decision support to localize regions of high risk concerning different agricultural pests. Abandonment of agricultural land, overgrazing, reed drainage, and other land-changing activities have to be monitored and updated regularly and considered under the aspect of known habitats of dangerous locust types. Nowadays, open-source remote sensing data and cloud computing possibilities provide multiple opportunities for regular monitoring of vast affected regions. In combination with additional information about soil types, relief, and meteorological situation, experts could exploit the information provided by remote sensing data analyses as additional support for preventive management.

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CHAPTER 6

6 Application of geospatial and remote sensing data to support locust management

Abstract

Negative impacts on agricultural activities by different locust species are well documented and have always been one of the major threats to food security and livelihoods, especially for local communities. Locust management and control have led to less frequent and intense plagues and outbreaks worldwide. However, political insecurity and armed conflicts affect locust management, and can as well as changing climate, and land use management contribute to new outbreaks. In the context of the increasing world population and higher demand for agricultural production, locust pests will remain of high concern. Geospatial and remote sensing data have become an important source of information for different applications within locust research and management. However, there is still a gap between available information and actual practical usage. In this study, we demonstrate the importance of geospatial and remote sensing data and how this information can be prepared for a straightforward application for stakeholders. For this purpose, we use the h3-hexagonal hierarchical geospatial indexing system to simplify and structure spatial information into standardized hexagon units. The presented concept provides decision makers and ground teams with a simplified information database that contains area-wide information over time and space and can be used without detailed geospatial knowledge and background. The concept is designed for the use case of Italian locust management in the Pavlodar region (Kazakhstan) and based on actual practices. It can be extrapolated to any other study area or species of interest. Our results underline the importance of actual land management on locust presence. Up-to-date land management information can be derived from time-series analyses of remote sensing data. Furthermore, essential meteorological data are used to generate locust-specific climatic characteristics within the h3-system. Within this system, areal prioritizing for locust management can be achieved based on the included spatial information and experience from ongoing practices.

6.1 Introduction

Locust plagues, upsurges and outbreaks around the world have always been one of the major threats to agriculture and food security (Gay et al., 2021; Kietzka et al., 2021). The history of reported damages affecting humans from large-scale, long-lasting plagues and upsurges of desert locust (*Schistocerca gregaria*) in Africa and Asia to country-wide and regional outbreaks of many other locust species (e.g. Australian plague locust (*Chortoicetes terminifera*), migratory locust (*Locusta migratoria*), Italian locust (Calliptamus italicus), South American locust (*Schistocerca cancellata*), Moroccan locust (*Dociostaurus maroccanus*)) is long and goes back to ancient times (Cullen et al., 2017; Latchininsky, 1998; Trumper et al., 2022; Zhang et al., 2019).

Since the 1960s, the development of preventive locust control strategies and usage of chemical treatments has enabled handling of outbreaks and plagues more effectively (Gay et al., 2021). Within these preventive locust control strategies satellite remote sensing has become an important data source for forecasting and monitoring favorable ecological conditions for locust development, as well as for mapping and assessment of locust habitat states (Cressman, 2013; Deveson, 2013; Hunter et al., 2008; Klein et al., 2021; Latchininsky, 2013; Piou et al., 2019; Zhang et al., 2019). Nowadays, different satellite sensors provide a tremendous amount of data which offer cost-effective options to derive geospatial information and use them to describe environmental changes and their causes. They are also used as input data for modelling in earth and environmental sciences (Chaminé et al., 2021). Especially the recent improvements in remote sensing (e.g., open access, increased spatial and temporal resolution, analysis-ready data, and big data applications) allow continuous and more detailed monitoring of complex environmental systems such as habitats of locust species and their dynamics in relation to environmental changes. Estimation of spatial distribution and habitat suitability has become possible by coupling geospatial data (e.g. remote sensing, climate, soil, relief data) with presence and absence in situ information (Aragón et al., 2013; Gómez et al., 2021; Klein et al., 2022; Malakhov and Zlatanov, 2020; Piou et al., 2013). Additionally, geospatial and remote sensing data are highly essential for locust management and for analyzing the impact of climate change on locust spatial distribution and potential future outbreaks (Meynard et al., 2020, 2017; Popova et al., 2016; Tratalos et al., 2010; Wang et al., 2019). One of the main goals of locust management is the assessment of outbreak risk, by continuous monitoring of affected regions and state of the locust population, and the prioritization of exposed areas in terms of required measurements.

Despite increased usage in applied geoscience and growing business services (e.g., agriculture, forestry, rapid mapping), there is still a gap between academic state of the art, technical possibilities and actual application of remote sensing and geospatial data with respect to locust management. The activities of the Australian Plague Locust Commission (APLC) and Food and Agriculture Organization of the United Nations (FAO) in the context of Australian plague and desert locusts, are two prominent examples demonstrating that the utilization of geospatial and remote sensing data effectively support locust management (FAO, 2022; Mangeon et al., 2020; Matthews, 2021). Managing various geoscientific data and understanding the corresponding specifications including data format, projection, spatial and temporal resolution, as well as data accuracy and limitations, usually requires several years of practice and experience. Since locust ground teams and decision makers undergo a different education compared to geospatial data analysts, there is often a discrepancy between available information from geoscientific data and possibilities and “real-life” practice of locust management. At the same time, a lack of ground data or poorly collected information affects locust management decisions and might even seize up the whole management chain (Gay et al., 2021). Therefore, it is of significant importance to prepare spatial information in a way that enables a straightforward application for a targeted group of users within locust management.

In this study, we use locust management, which requires knowledge of multiple environmental disciplines (e.g., entomology, meteorology, agronomy) as a use case to demonstrate how geospatial information can be processed to allow for an improved implementation and provide additional information sources. For this purpose, we use the h3-system to simplify spatial information, and prioritize areas by means of decision trees and thus support decision making (Bousquin, 2021; Kang et al., 2021; Uber Technologies Inc., 2018). The h3-system has been proven to be of advantage when combining a complex set of information in the framework of a regular Discrete Global Grid (DGG) which is unbiased concerning spatial patterns and allows the development of simple and efficient algorithms (Li, et al., 2022; Sahr et al., 2003). In this study, different spatial information relevant for locust management are processed and presented in a stepwise approach to provide additional information for decision-making and field monitoring. Within the presented approach, complex information derived from various geoscientific datasets, including remote sensing imagery and climatic variables, are summarized at simplified hexagon levels which can be exploited by diverse set of rules according to current situation and severity of increase in locust population.

This paper is structured as follows. First, we provide background information on the typical life cycle of locusts. In addition, fundamental details with respect to the monitoring and management of the Italian locust are illustrated using the example of Pavlodar region, located in north-eastern Kazakhstan. Second, we recap which kind of information can be derived or is available from remote sensing data and other geospatial information sources. In the third and fourth section, we introduce how these datasets are pre-processed using the h3-system and how they can be used by ground teams to receive relevant and understandable information, thus allowing them to take fast decisions on a spatially aggregated level. Finally, the importance of geoscientific data for locust management is discussed in the light of climate change and applied control measurements.

6.2 Background information

6.2.1 Italian locust ecology and life cycle

Locusts are grasshoppers in the family Acrididae which are characterized by the so-called phase polyphenism (Trumper et al., 2022). At low density, the locusts behave as solitarious individuals and are an important part of their ecosystem (Cullen et al., 2017; Latchininsky et al., 2011). The phase change is initiated by a combination of different ecological conditions which benefit increasing locust population. During this, so-called gregarious phase, locusts behave in groups which leads to band formation of nymphs and later migrating swarms of adults (Trumper et al., 2022). Also, many locust species appear even in different colors and sizes during gregarious phase (Uvarov, 1957).

The CIT is an intermediate form between typical gregarious and solitarious acridid species (Sergeev, 2021). It is a univoltine species with egg diapause during autumn and winter. Its habitats are found in dry steppes and semi-desserts with preferable plants such as wormwood and sage-brushes (Artemisia spp.) and moderately compact, sandy soils (Sergeev, 2021). Potentially, CIT can be found up to 2700 m altitude and prefers abandoned or fallow land, pasture, active agricultural field borders and is also found along infrastructure tracks such as roads and railways (Kambulin, 2018; Sergeev et al., 2022). Generally, CIT is a highly elastic species and tolerates a wide range of semi-arid climate and soil types (Sergeev et al., 2022). After winter diapause, the hatching starts in late spring depending on local meteorological conditions. Higher air temperatures and less precipitation, which affect local edaphic situation lead to an earlier hatching start. On the contrary, cool temperatures and unnormal high rain amounts, at the location of egg-pods, lead to a later start as well as decreased population due to higher egg mortality. Once the nymphs hatch, they undergo five instar states whereas each state lasts for 3-7 days. The duration and population size, is again, controlled by meteorological conditions and food availability. Higher temperatures favor a faster development (Sergeev et al., 2022). Nymph bands of CIT can move up to 155 m per day. Once the locusts reach adult state and are capable to fly, their location is less predictable. With wind, large CIT swarms are capable of flying more than 200 km per day, while smaller swarms fly up to 20-40 km (FAO, 2021). After the pairing period which takes place around July and August (Figure 6-1), the female locusts lay up to six egg-pods (containing 20-60 eggs, mostly 30-35) and a new life cycle of the next locust generation begins (Sergeev et al., 2022).

Figure 6-1. Italian locust; left: mating, middle: oviposition, right: egg-pod. Photos from 27.07.2022 (50.3 N 75.44 E).

6.2.2 Locust management in Pavlodar region, Kazakhstan

The major CIT outbreak in 1999/2000 caused a total damage of 220,000 ha grain crops and an estimated economic cost of 15 Mio. US$ (Latchininsky, 2013). Within this period almost 10 Mio. ha land (approx. 8 Mio. in Kazakhstan) were treated with pesticide (Kambulin, 2018). The reason for such a large-scale and intense outbreak was a lack of preventive locust management at that time combined with a change of land use practices during the 1990s (Kambulin, 2018; Sivanpillai et al., 2009). Vast areas of former agricultural and pasture land were abandoned and developed into a perfect habitat for CIT which led to an increasing locust population over several years. Land management can change very fast due to different driving factors (e.g. political programs, economic profits, security, climate change) and can create perfect conditions for locusts breeding and population increase (Zhao et al., 2020). Therefore, up-to-date information on land cover and land use considering different locust pests have a high potential to support locust management.

After this outbreak, preventive management has been reestablished and has become a key component in controlling and avoiding locust outbreaks and related damages. In Kazakhstan, preventive management is done by regional offices under the coordination of a state inspection committee in the agricultural sector of the ministry of agriculture. The "Pavlodar regional branch of SD Republican Methodological Center of phytosanitary diagnostics and forecasts" is responsible for field monitoring, reporting and forecast of the CIT development in Pavlodar region (Figure 6-2). This branch provides forecasts and assessments which are the base for annual preventive area treatment to avoid an increase in locust population and keep it under control. Field officers are using Global Positioning System (GPS) and standardized protocols to monitor qualitative and quantitative parameters of locusts four times a year (spring egg-pods control, spring nymphs hatching, summer pairing and egg-laying, autumn egg-pods control). For this study, a total of 1515 presence locations indicating CIT breeding spots collected between 2016-2021 was used to analyze favorable LCLU situation where egg-pods were laid and hatching occurred.

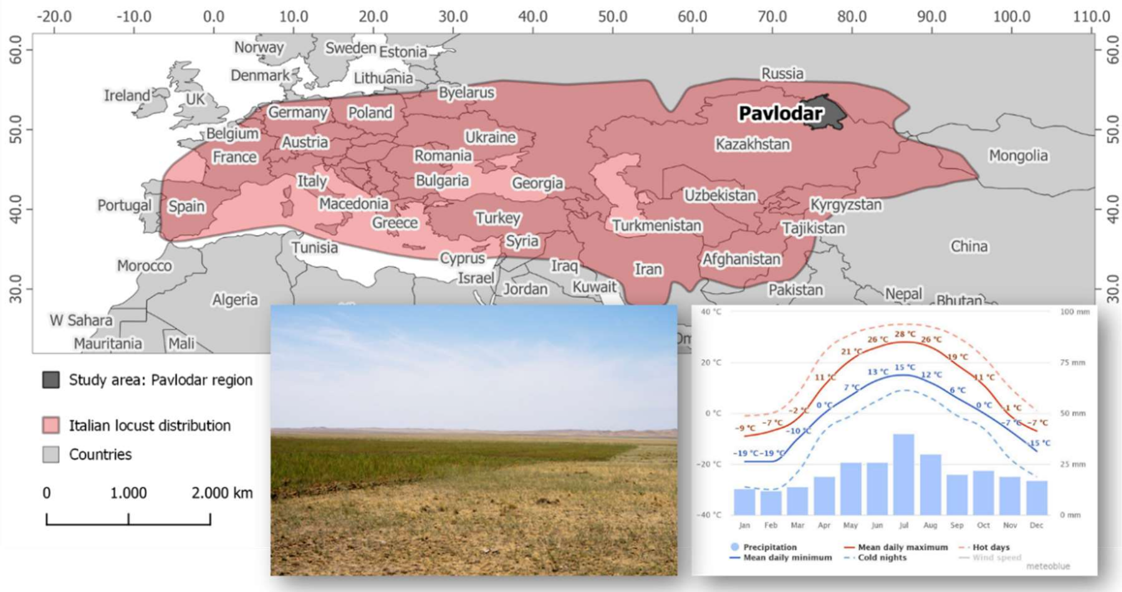

Figure 6-2. Overview of study area and Italian locust distribution (based on Fig. 14 from Sergeev et al., 2022). Photo: Typical habitat (from 27. July 2022, 50.3 N 75.44 E). Climate diagram for Pavlodar (source: meteoblue.com).

6.3 Methods

6.3.1 Remote Sensing Data and Geospatial Information for Locust Management

Since locust development is highly dependent on the state of its ecosystem, meteorological conditions and land use practices, there is a vast number of existing datasets which can be used for locust management. First of all, locust presence and abundance locations from field data in combination with spatial information data can be applied to analyze and estimate species richness and spatial distribution as well as potential habitats and their suitability (Klein et al., 2021; Lazar et al., 2015; Piou et al., 2017; Youngblood et al., 2022; Zhang et al., 2019). Second, the monitoring of the actual situation and the forecast of the hatching begin and possible outbreaks which are based on meteorological data, soil conditions as well as vegetation state are the most important components for early warning (Cressman, 2016, 2013; Lecoq, 1995; Lecoq and Cease, 2022; Liu et al., 2008). Based on a literature review of relevant studies, we use a selection of the most important variables for CIT presence and development which are summarized in Table 6-1.

In detail, we used Sentinel-2 and Landsat imagery to derive a land cover and land use map (Figure 6-3). The processing and classification of remote sensing imagery was conducted on the Google Earth Engine (Gorelick et al., 2017). Due to the limited availability of Landsat imagery over this region, we generated median composites covering a 5-year period between 1984 and 2020 (i.e. 1984-1989, 1990-1994, 1995-1999). Besides the spectral bands, the spectral indices normalized difference vegetation index (NDVI), modified normalized difference water index (MNDWI), salinity index (SI), and normalized difference built-up index (NDBI) were included. Using the Random Forest classifier (Breiman, 2001), agricultural areas were mapped in each of the Landsat composites. Likewise, a median composite was created using Sentinel-2 imagery for the year 2021. Here, all Sentinel-2 bands were resampled to 10 m spatial resolution. The resulting classification map covers the classes agricultural land use, bare soil, sparse as well as dense vegetation, and for completeness built-up areas. At this, agricultural and built-up areas were extracted from the ESA WorldCover classification (Zanaga, D. et al., 2021). Based on the temporal evolution of agricultural land use from the Landsat composites and the recent classification of agricultural land use in 2021 from the Sentinel-2 imagery an intersection was performed to retrieve abandoned land. Next, the Landsat-based abandoned land class is resampled to 10 m spatial resolution to match the Sentinel-2 classification.

Furthermore, the employed meteorological variables are gathered from the ERA5-Land reanalysis (Hersbach et al., 2020; Muñoz-Sabater et al., 2021) and the TerraClimate dataset (Abatzoglou et al., 2018). Temperature data at daily temporal resolution was required to calculate the sum of effective temperature (SET). In this regard, hourly ERA5-Land temperature was aggregated to daily temporal resolution (Figure 6-3). In addition, precipitation, soil moisture, and temperature at monthly temporal resolution were retrieved from TerraClimate due to its comparatively high spatial resolution. In the context of Central Asia, both ERA5 and TerraClimate data are widely applied (e.g. Hao et al., 2022; Hou et al., 2022; Hu and Han, 2022; Li et al., 2021; Shi et al., 2020; Zheng et al., 2021).

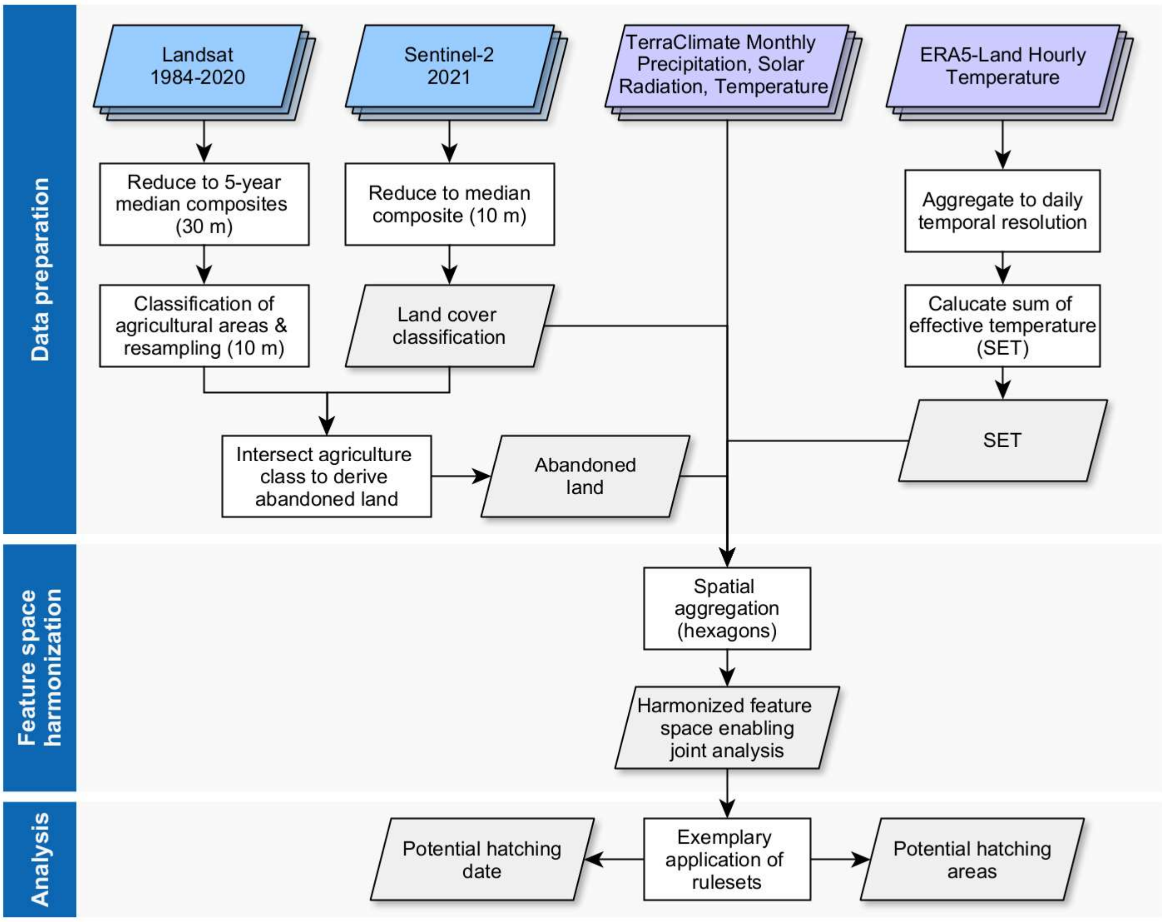

Figure 6-3. Workflow including classification steps and spatial aggregation to achieve harmonized data within hexagon grid system.

Table 6-1. Important variables for CIT and used open source geospatial and remote sensing datasets.

Variable	Spatial res.	Temporal res.	Source/Reference
Abandoned land, agriculture, natural vegetation (bare, sparse, dense)	10 m	Annual	Classified based on annual Sentinel-2 time-series phenology analyses of the year 2021 compared to long-term phenology of 1984-2020 (Landsat archive)
Temperature	10 km	Hourly	ERA5-Land (Hersbach et al., 2020; Muñoz-Sabater et al., 2021)
Temperature	4.6 km	Monthly	TerraClimate (Abatzoglou et al., 2018)
Precipitation	4.6 km	Monthly	TerraClimate (Abatzoglou et al., 2018)
Soil Moisture	4.6 km	Monthly	TerraClimate (Abatzoglou et al., 2018)
CIT nymph presence	Lat, Lon	Annual (2016-21)	Pavlodar regional branch

6.3.2 Data harmonization workflow

In order to enable a joint analysis of the collocated geospatial data, a harmonization in terms of their spatial resolution is required. In this section, we demonstrate the spatial aggregation based on a hexagon-system and how it can simplify the interpretation and decision-making without detailed background knowledge of each individual dataset characteristics (e.g. data formats, temporal or spatial aggregations, reprojections, etc.). Nevertheless, despite introduced simplification of handling geospatial datasets, all potential users shall be informed and aware about existing range of uncertainties and possible errors coming along with geospatial and remote sensing datasets. DGGs such as the hierarchical geospatial index h3-system allow simplified and effective data combination and spatial interpretation (Sahr et al., 2003; Uber Technologies Inc., 2018). In this study, we apply the h3-system which offers a quick aggregation at different levels across disparate datasets independent from precision and data specification (spatio-temporal resolution, projection, format). Furthermore, the hexagon system enables grid-based algorithm development focusing on spatial relation between grids. Compared to triangles or squares grid systems, hexagons have the same topological relation and are in equidistance between all neighbors (Uber Technologies Inc., 2018; Ma et al., 2021). In addition, due to the hexagonal shape, a smaller number of grids is required to represent the raster data, reducing the processing time and storage space (Duszak et al., 2021). Regarding locust management, which requires a lot of different parameters as described in the previous section, the application of such systems has three main advantages. First, different dataset characteristics and data pre-processing do not have to be done by ground teams and end users. Second, simple spatial analysis assessment and interpretation can be done straightforwardly based on defined conditions and expert knowledge for specific applications at different hierarchical levels. Third, existing spatial relationships between grid cells (e.g., distances- and nearest neighbors-based conditions) can be exploited for more complex assessment. Figure 6-4 shows the h3-system for the Pavlodar region at three levels with moderate area size.

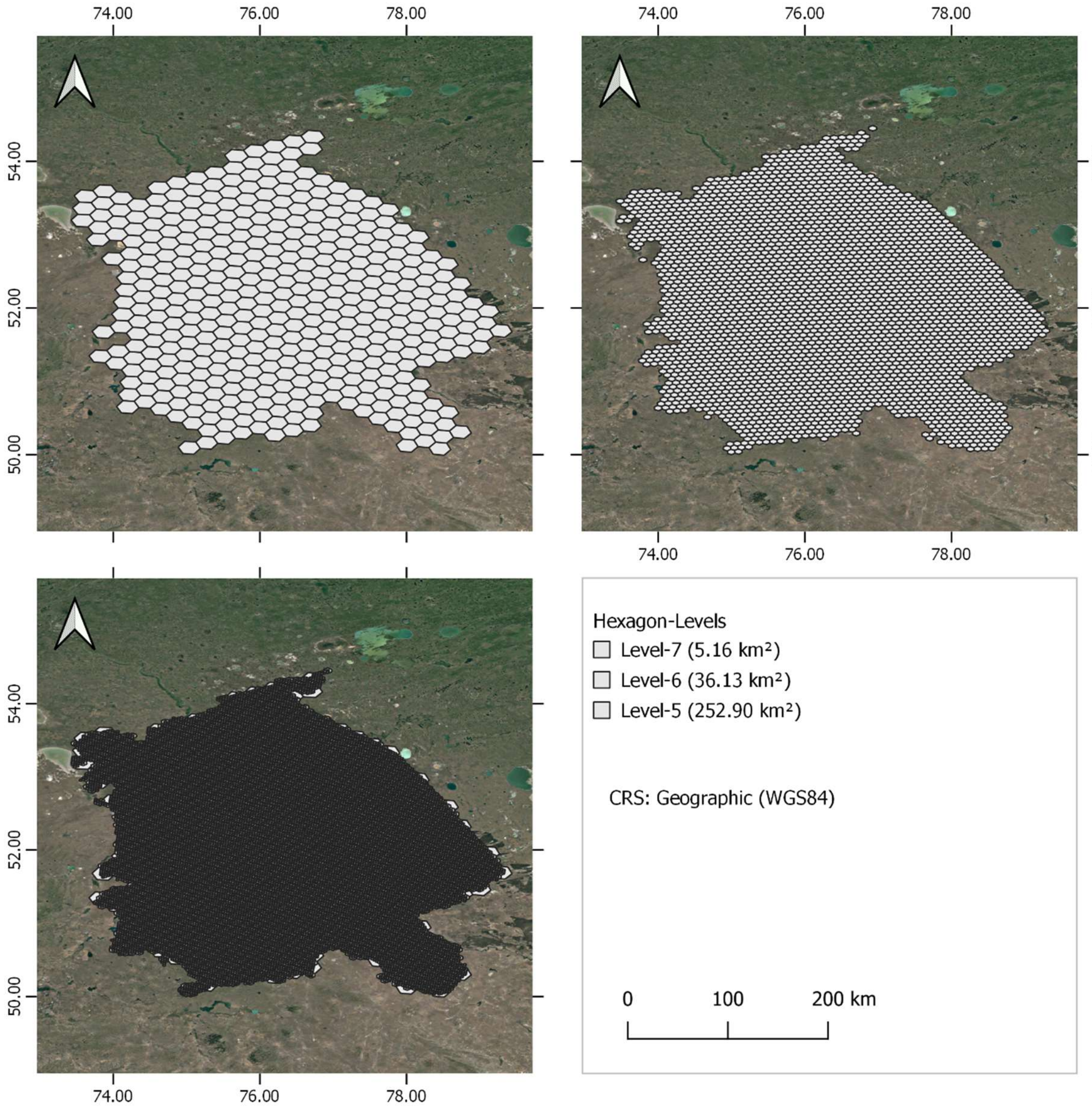

Figure 6-4. Pavlodar region in three different spatial resolutions with approximate individual hexagon areas of: level-5 (top left), level-6 (top right), and level-7 (bottom left).

After the selection of an appropriate level and hexagon area for the use case based on the h3-py python software package, all geospatial data are spatially aggregated to the hexagons using the average function of zonal statistics. At this point, the geospatial and remote sensing datasets are harmonized to the same spatial unit and geographic projection. From here on the end-user and experts can apply their regular data analysis on large scales and entire territory of interest or define and develop new rulesets and algorithms by exploiting the full range of available geospatial information. In this study, we demonstrate an exemplary working process based on essential characteristics of CIT in the Pavlodar region. Figure 6-5 presents a schematic stepwise workflow which combines different exemplary parameters to exclude areas of minor risk as well as prioritize hotspot regions based on highly favorable bio-climatic, edaphic and land surface conditions.

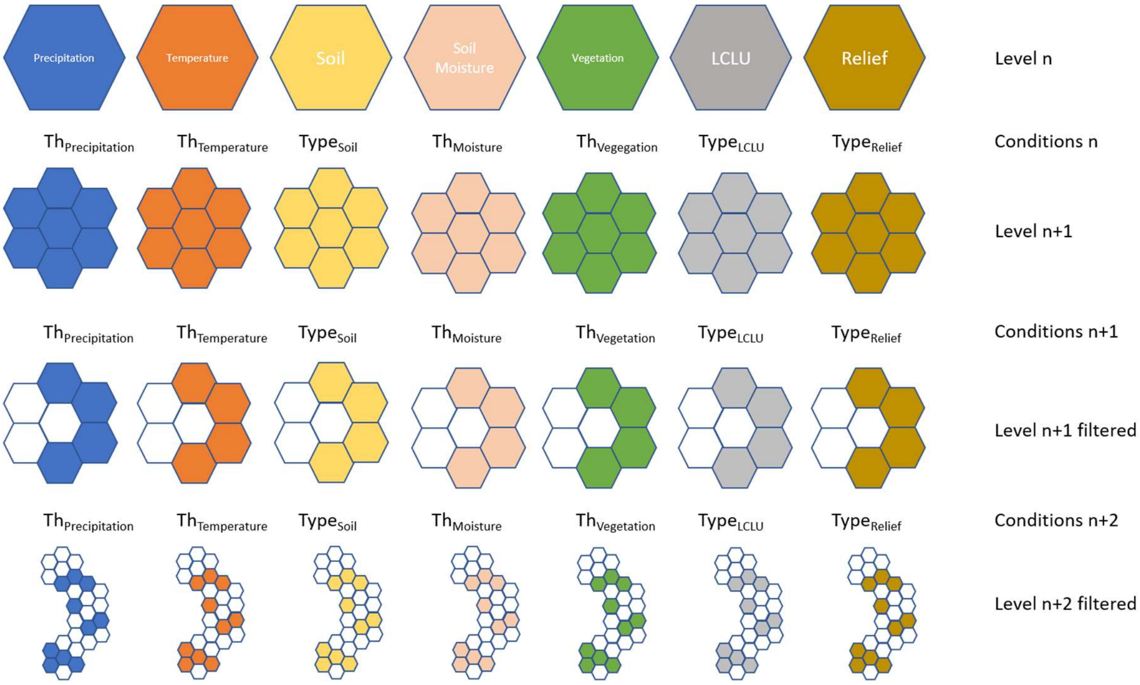

Figure 6-5. Schematic exemplary stepwise workflow to use h3-polygons at various levels to prioritize hotspot areas (Th = threshold). Variables, appropriate levels, and conditions shall be defined based on individual specifications of species and application tasks.

6.3.3 Use-case for Italian locust

As described in section 2, the development of CIT depends highly on four main influencing factors. First, the local meteorological conditions (temperature and precipitation) which determine egg mortality, survival of young nymphs within first locust instar phases, as well as the duration of development phases. Furthermore, meteorological conditions also determine the beginning of hatching and availability of green vegetation for feeding. Second, human land management directly affects the presence or absence of locusts. Active land management and ploughing lead to mechanical destruction of egg-pods and reduce the locust population (Latchininsky, 2013, 1998; Sergeev et al., 2022). On the other hand, fallow and abandoned land become an ideal habitat for further distribution and increase of locust population. The information on land cover land use (LCLU) can be derived by time-series analyses of remote sensing data and annual comparison of vegetation development because most cultivations are characterized by distinct phenological cycles (sowing, growing, harvesting). Therefore, active agricultural fields differ from rangelands and natural vegetation. Third, the mid- and long-term climate conditions affect the biological increase or decrease of locust populations. Drought years (high temperature and low precipitations) usually favor the development resulting in population increase. Cold and wet years decrease the population (Kambulin, 2018; Tronin et al., 2014). Finally, static environmental conditions such as soil type and relief must be considered as well. All four influencing factors are independent of locust management and must be put in logical context for monitoring and forecast purposes. Furthermore, one has to keep in mind that the locust population dynamics are highly influenced by active ongoing control measurements and their effectiveness. Favorable meteorological conditions over several years can be counteracted by extensive monitoring and pesticide treatments to avoid exponential population increase.

In the Pavlodar region, the meteorological conditions can be described based on Selyaninov's hydrothermal coefficient (HTC) (Selyaninov, 1928). The HTC has been applied in different studies related to drought determination (Dabrowska-Zielinska et al., 2020; Ryazanova and Voropay, 2019; Vlăduţ et al., 2017), as well as to assess the favorability of climate for the development of cultivations and natural plants (Evarte-Bundere and Evarts-Bunders, 2012; Kwiatkowski 2015; Leblois and Quirion 2013). The HTC during vegetation period (HTCVP) is calculated based on the following formula:

$$HTC = \frac{10\sum_{i=1}^{n} P_i}{\sum_{i=1}^{n} T_i}$$

where *n* is the length of the period (months) when mean temperatures exceed 10 °C, *Pi* is the precipitation amount (mm) of the *i*th month, and *Ti* is the average air temperature (°C) for the *i*th month.

Furthermore, the SET is another important indicator to access meteorological conditions which influence locust population increases or decreases. The SET is calculated based on the following formula:

$$SET = \sum_{i}^{n} T > 10°C$$

where *i* - *n* is the period between January 1st to December 31st and *T* > 10°C mean daily temperature above 10°C.

A population increase of CIT is expected to be favored in dry and hot years without exceptionally high precipitation amounts in spring. We summarized optimal conditions and logical rules based on (Kambulin, 2018; Sergeev et al., 2022) (Table 6-2, Figure 6-6).

Table 6-2. Logical rules for CIT population dynamics in the Pavlodar region based on ongoing meteorological conditions[1].

Conclusion	HTC_{VP}	SET	Annual Precipitation	Seasonal Condition
Highly favorable years	0.3-0.5	2800-3100°C	150-200 mm	spring precipitation is within LTA
Generally favorable years	0.5-0.7	2250-2800°C	<250 mm	spring precipitation is within LTA
Population decreasing years	> 0.5	<2800°C	> LTA	exceptionally wet and cold years, especially during springtime as it negatively affects the survival of the eggs and nymphs, spring precipitation >LTA, spring temperature <LTA

[1]LTA=long term average based on 1991-2021 data. Conditions should be considered within a logical "&" function.

In conclusion, a population increase begins with hot and dry years and its progression depends on the meteorological conditions of the following years. In this context, (Tronin et al., 2014) presented the dependency on drought years for CIT in West Siberia. Comparable assumptions are also formulated for Northern and Western Kazakhstan (Kambulin, 2018). In this regard, it has to be mentioned that different authors postulate that drought years and locust outbreaks are related to the solar cycle (Cheke et al., 2020; Kambulin, 2018; Sergeev et al., 2022; Tronin et al., 2014).

Additionally, based on SET during the spring and early summer period, the start of hatching (SoH) can be estimated. Here, the accumulation of SET starts after the daily mean temperature reaches above 0°C in five consecutive days, whereas only those temperature values are summed up which are above 10°C. The hatching is assumed to begin once the SET threshold reaches 90°C. In praxis, the field officers already start monitoring the egg-pods when the threshold reaches 70°C. Around that time the embryonal state of eggs is examined by field experts which enables more accurate start of hatching estimation.

$$SoH_{CIT} = \sum_{i}^{n} if\ T > 10°C\ then + T - 10$$

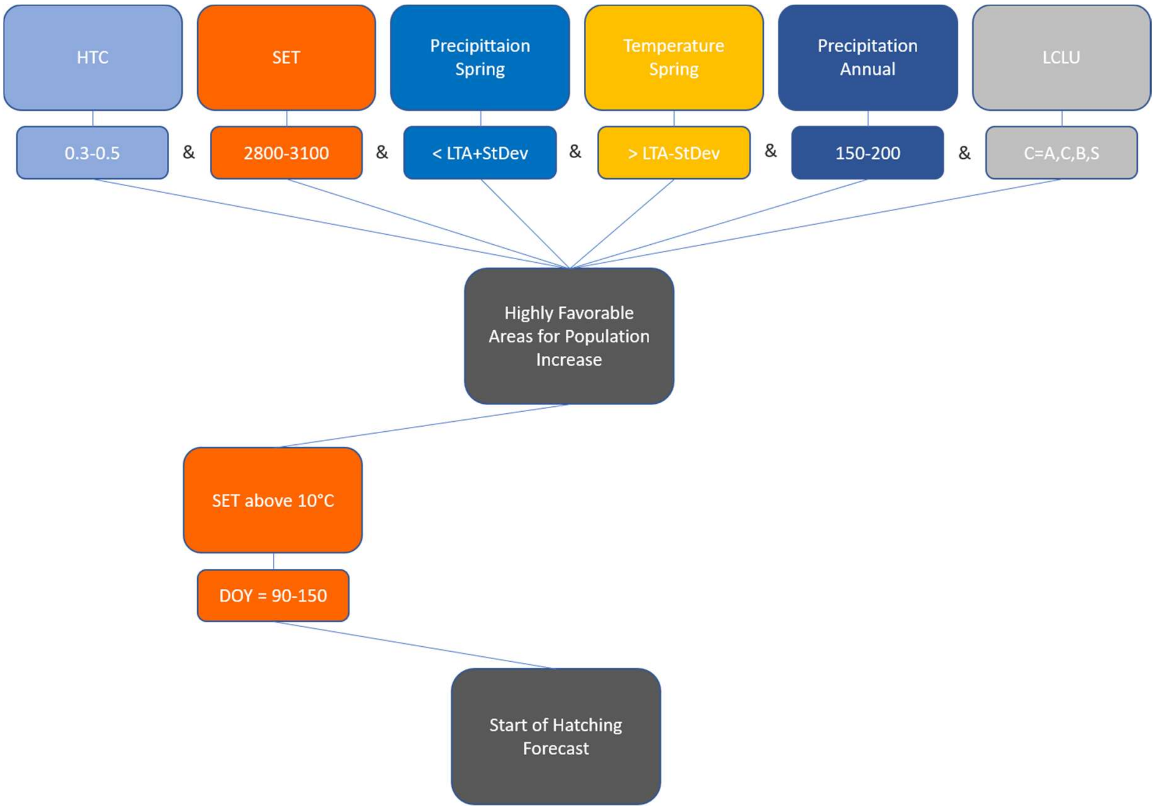

Figure 6-6. Highly favorable meteorological conditions for potential CIT population increase. For Pavlodar region based on (Kambulin, 2018; Sergeev et al., 2022), including SoH forecast. (LTA=long term average based on 1991-2021 data, A=abandoned land, C=recently or currently used for agriculture, B+S=bare soil and sparse vegetation mosaics.

The population dynamics correspond to the effects of seasonal meteorological conditions on the life cycle of CIT. During rainy and cold springs, the egg mortality is high, and hatching is delayed. In contrast, dry and hot conditions secure egg survival and accelerate hatching. During long, hot, and dry summers multiple mating is favored which also contributes to population increase. On the other hand, high precipitation during autumn in combination with low temperatures endanger newly laid eggs by fungi and mold (Kambulin, 2018).

Usually, the field officers receive weather information from local stations and plan their monitoring according to the actual situation which varies from year to year in terms of timing as well as region. The defined conditions are based on experts' knowledge and their daily practices from the “Pavlodar regional branch of SD Republican Methodological Center of phytosanitary diagnostics and forecasts” and detailed information from the FAO report which was written by leading entomologists and CIT experts (Sergeev et al., 2022). The ruleset can be adjusted in any way and extended by additional parameters and conditions.

6.4 Results

6.4.1 The importance of land cover for breeding locations

The CIT ecology is more complicated compared to other locust species (Latchininsky, 2013; Sergeev, 2021; Tronin et al., 2014). There are no specific ecosystems which represent the natural habitat of CIT and this is one of the main reasons why remote sensing-based monitoring of spatial distribution and locust population density is more difficult. However, one of the most crucial factors for CIT breeding sites and population increase are the state of the land surface and its management. It is well documented that different locust species, especially CIT, find perfect conditions on abandoned land or fallow fields (Kambulin, 2018; Latchininsky, 2013; Sergeev et al., 2022; Sivanpillai et al., 2009; Zhao et al., 2020). In this study, we quantified the relationship between the occurrence of abandoned land and the presence of CIT based on time-series analyses using Landsat and Sentinel-2 data. An up-to-date land cover and land use map of 2021 was generated (Figure 6-7a). Besides the actual state of the land surface in 2021, Figure 6-7 includes spatial and temporal information on abandoned land and fallow fields evolution (Figure 6-7b) and indicates the transformation of these areas (Figure 6-7c). In combination, the derived information provides, whether areas were used for agricultural purposes in the past and the time when agriculture activity stooped, as well as its recent land cover situation. The generated LCLU map based on Sentinel-2 imagery for the year 2021 resulted in an overall accuracy of 86.02% and a Kappa coefficient of 0.824. The binary cropland classification has an overall accuracy of 96.48% and a Kappa coefficient of 0.877.

The intersection of field data locations with derived LCLU information shows that 63% of CIT presence data were found on land which was classified as formerly or recently used for agriculture (36% abandoned land; 27% cropland). Another 36% are distributed across bare to sparse vegetation mosaics (13% sparse; 23% bare). Most breeding locations found on abandoned land were detected in areas which became abandoned or fallow in the period 2016-2020 (62%) and 2011-2015 (15%). This underlines the hypothesis that annual changes in land use and land cover directly influence locust population dynamics because of changes in nutrient availabilities (Cease et al., 2012; Le Gall et al., 2019; Youngblood et al., 2022). Furthermore, it is not only important to derive the age of abandoned land to assess its succession state but also the present land surface situation which means, whether the fields have turned to bare soils, sparse or dense vegetation mosaics. In this regard, 38% of CIT breeding locations were found in sparse vegetation and 62% in bare soil mosaics. These results are in line with descriptions from literature about preferable land cover and bare soil-vegetation mosaics for egg laying of CIT and young fallow fields (Sergeev et al., 2022).

6.4.2 The importance of meteorological conditions for breeding locations and population dynamics

As discussed in the previous section meteorological conditions are the most important variables which define the timing of the life cycle as well as locust population dynamics. Therefore, climatic conditions determine whether locusts are in the solitarious or gregarious phase. Figure 6-8 illustrates the results of relevant meteorological variables at h3 hexagon level-7 for the year 2021. The annual SET provides valuable information about which areas have experienced ideal thermal conditions over the year of interest (Table 6-2). Therefore, the dark orange areas (Figure 6-8a) experiences highly favorable thermal conditions to promote locust population increase over the year 2021. In 2021 central and south Pavlodar regions as well as the region east of Irtysh river show higher spring temperature (Figure 6-8b) and dryer conditions (Figure 6-8d). This is critical especially for the areas east of Irtysh river which are well known contain hotspots for CIT breeding (Kambulin, 2018; Sergeev et al., 2022). Despite the conditions during spring period, the annual precipitation (Figure 6-8c) also affects the development of locust. Furthermore, extreme rain events negatively affect young nymphs. Additionally, each hexagon contains both, the climatic history and ongoing conditions which enable a comprehensive view in terms of locust situation in the past. Figure 6-9 presents climatic characteristics over the past 30 years for four selected hexagons with regards to CIT-relevant parameters. In fact, recent population increases within the study area are also mirrored by climatological variables. For example, there was drier period with significantly less annual precipitation (6-9e) and HTC (6-9a) lower than 0.5 the years before the 1999-2001 outbreak, as well as before 2011-2012 and 2018 population upsurges in Pavlodar. These actual years with higher locust population are characterized by higher than average spring temperature (6-9f) slightly above average soil moisture and spring precipitation (6-9c, 6-9h).

In general, locust managers are monitoring all relevant variables in combination to assess whether the situation based on recent climate, ongoing meteorological conditions and actual land cover situation provide higher risk for population increase. Spatial data preprocessing within presented h3 hexagonal system provides an easy to use database at different spatial levels. Based on hexagonal units, locust managers can access and assess all necessary information in a standardized way. The different variables are spatially harmonized so that current areas with favorable or less favorable conditions can be easily identified.

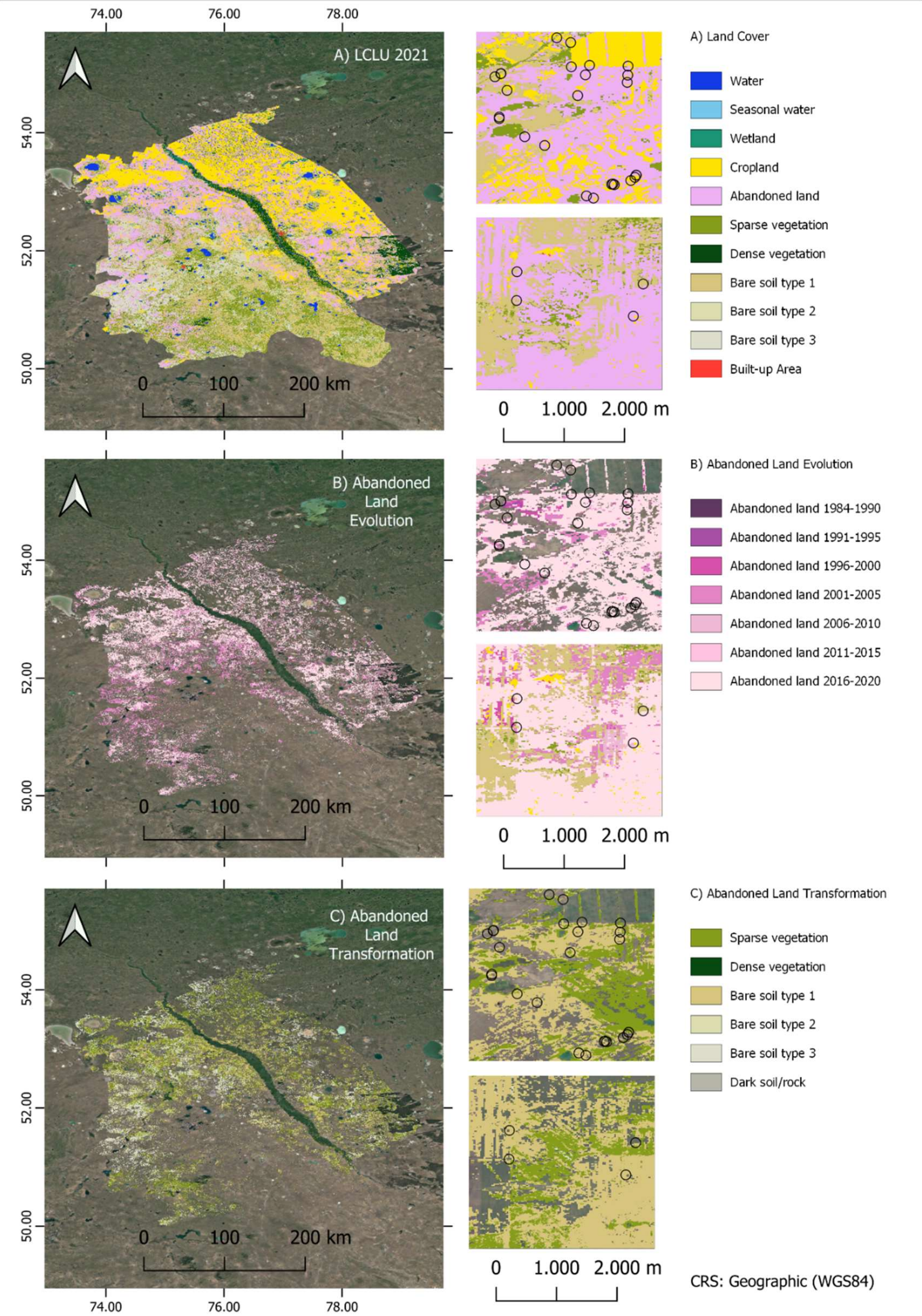

Figure 6-7. LCLU classification and derived parameters for abandoned land evolution and transformation. Including two detailed views and detected nymph locations 2016-2021 (circles).

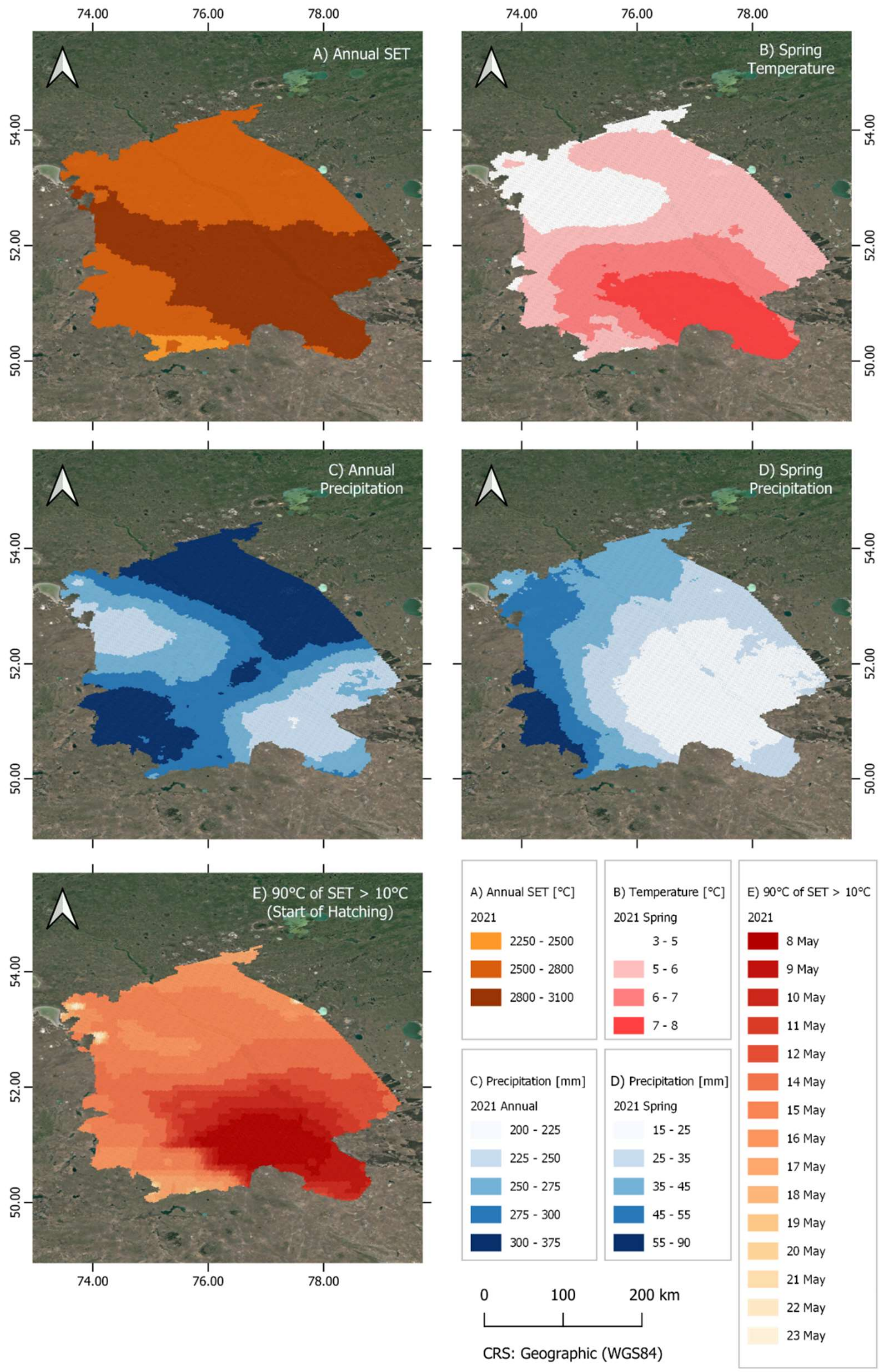

Figure 6-8. Climatic characteristics with regards to CIT relevant information aggregated at level-7 hexagons (5.16 km²).

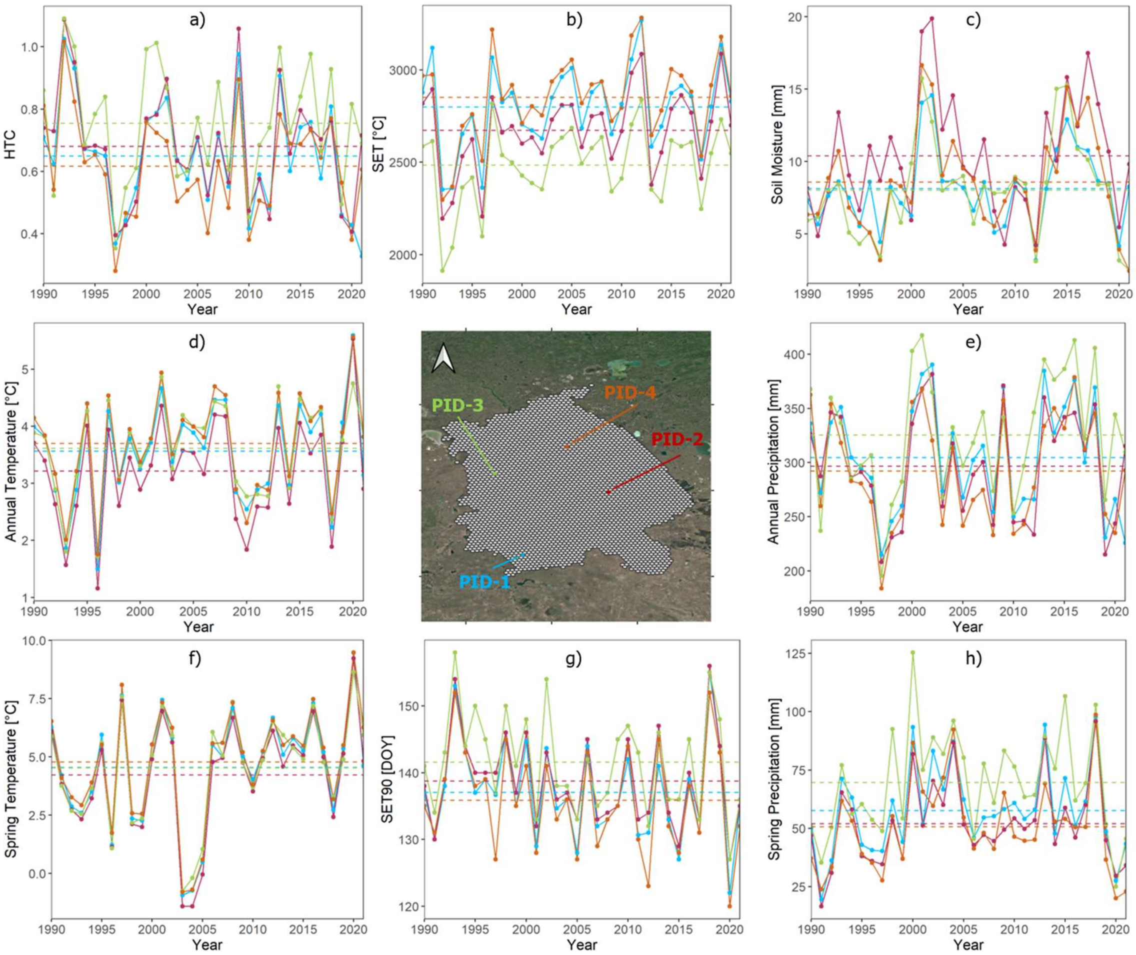

Figure 6-9. Exemplary climatic characteristics for four selected hexagons (polygon identification, PID) with regards to CIT relevant information (dashed lines= long-term average for 1990-2020).

6.5 Discussion

6.5.1 Importance of prioritization and hotspots

Gay et al. (2021) stated that the knowledge and prioritization of hotspot breeding sites is highly important to improve the capability to maintain plagues or outbreaks. In this way, attention and efforts shall be concentrated in time and space to enable highly effective preventive locust management. Therefore, it is crucial to reduce the area which has to be monitored by excluding areas where locust breeding and hatching are unlikely and to prioritize areas with different levels of urgency to allow stepwise actions and urgent intervention. Gay et al. (2021) conclude that any tool which supports guidance in this regard is helpful to reduce plagues and outbreaks. Besides historical ground data collection, consistent monitoring of ecological and meteorological conditions with remote sensing and geospatial datasets is inevitable. The presented approach demonstrates, how different geospatial and remote sensing datasets can be pre-processed for end-users so that they are simply applicable for locust management in a straightforward way. This allows assumptions from daily practices and fast decisions to either exclude or prioritize areas when time and resources are critical.

In this context, Boedeker et al. (2020) estimated that worldwide there are approx. 385 Mio. annual accidental poisoning cases including around 11.000 mortal cases related to pesticide usage. Despite improved practices and guidelines for pesticide treatment for locust control and outbreak fighting, the risk of poisoning is always present. Therefore, if preventive locust management works effective in terms of time and space, less pesticides under lower time pressure will be used during recessions and depressions phases to keep the locust population low and in its solitarious form. However, if locusts are already in gregarious phase the control measurements should occur during the nymph development phase before it is capable to fly and migrate. During this phase, locusts are in groups and bands and can be localized according to the positions of egg-laying from previous field monitoring. If locust management is functioning well, the ground teams are aware of locations with potential increasing locust density and the state of the locust life cycle (hatching, instar phase). Nevertheless, the treated areas against locust nymphs can be still exceptionally large (Figure 6-10). Despite ongoing research projects and developments for applying bio-pesticides, the ground control teams often use chemical pesticides which proved to be effective and affordable. The presented approach of identifying areas of high risk and prioritizing them for monitoring and treatment could thus contribute to an aerial assessment of ecological conditions and in this way improve health safety and reduce the usage of pesticides. This becomes of higher relevance when active locust management does not exist (e.g., due to insufficient funding, insecurity due to political conflicts, absence of locust outbreaks over decades) or locust swarms reach regions which usually are not affected and therefore not prepared. The most important component of preventive locust management is a functioning system with locust field officers operating in the field on daily basis (Gay et al., 2021). This is also of high importance for future efforts to improve modelling and remote sensing-based locust breeding mapping and damage assessment as it depends on availability and accuracy of ground data (e.g., correct species identification, precise geolocation, abundance and absence). However, this depends highly on the existing budget, accessibility to affected areas and security (Showler and Lecoq, 2021). Meynard et al. (2020) concluded that socio-political instability in the Middle East and East Africa contributed to the 2019-2021 outbreak of desert locusts. Lecoq and Cease (2022) summarized that the locust problem, associated measurements and research are a cycle of repeated events with increased interest of media and opportunistic scientific publications during and shortly after major outbreaks.

In regards to food security and the fact that locusts are a nutritious food source, historically and currently being consumed by humans (Kietzka et al., 2021), future outbreaks and plagues might become a valuable source of additional food as occurred during the last desert locust upsurge at a local scale (van Huis, 2021). However, in this case the insects for consumption should not be contaminated by pesticides.

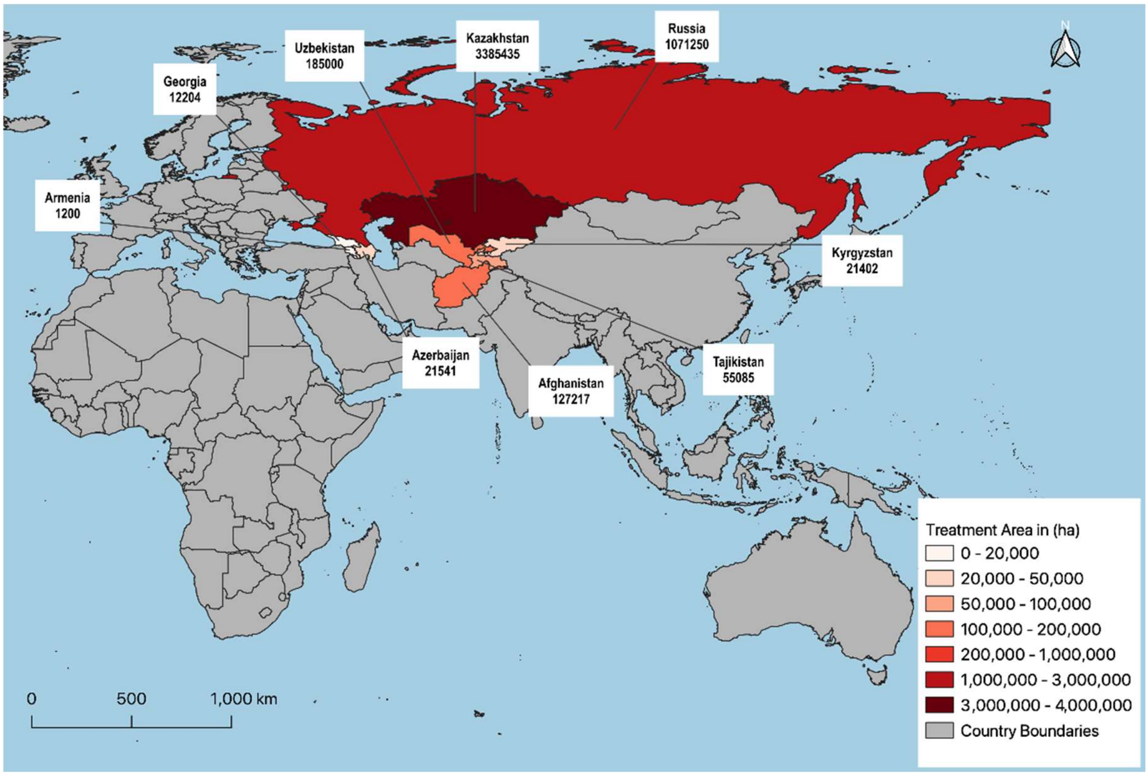

Figure 6-10. Treated cumulative area between 2010-2021 against Moroccan locust (DMA), Italian locust (CIT) and Asian Migratory locust (LMI) in Caucasus, Central Asia, and Russia (Information extracted from monthly FAO reports).

6.5.2 Geospatial data and accuracy

An accuracy assessment is conducted to provide the user with information on the error and uncertainty of the resulting output products (Lyons et al., 2018). These accuracy measures are crucial for using and interpreting the data (Brovelli et al., 2015; Stehman and Foody, 2019). In this regard, it is important to keep in mind that geospatial datasets and outputs derived from remote sensing data are only a generalization of the reality (Foody, 2002) and might come along with uncertainties. Due to this fact, users and decision makers need to be aware and have to understand that the derived information have to be considered critically and carefully in the light of the provided accuracy measures.

6.5.3 Future studies for climate change effects on locust species

Insect pests might destroy 10-25% more crops due to climate change (Deutsch et al., 2018). This is partly because climate change reshuffles northern and southern species within their niches (Antão et al., 2022; Çiplak, 2021; Youngblood et al., 2022). Apart from temperature changes, also the precipitation trends determine future occurrences of compound hot–dry events (Bevacqua et al., 2022) while increased frequency of global precipitation extremes with its influence on locust life cycles (Thackeray et al., 2022). For example, for desert locusts, the influence of climate change on tropical cyclone heavy rainfall is evident (Utsumi and Kim, 2022). As future climate will bring more droughts and more intense precipitation events (IPCC, 2019), it is also of high concern for many other locust species around the world (Cressman, 2016; Kimathi et al., 2020; Latchininsky, 2013; Meynard et al., 2020, 2017; Wang et al., 2019; Youngblood et al., 2022). However, as stated in Lecoq and Cease (2022) there is still a lack of detailed understanding of how different locust species will be affected by climate change. Therefore, further assessment of the impacts of climate change on locust habitats and population dynamics and adjustments to locust management and control are of high importance not only for the most dangerous species such as desert locust, migratory locust, or Australian plague locust but also for other species with regional or even local relevance. The recent outbreaks of Moroccan locust (*Dociostaurus maroccanus*) in Sardinia, Italy and Tajikistan, migratory locust (*Locusta migratoria*) in Romania, or brown locust (*Locustana pardalina*) in South Africa are only few of many examples that locust pests can become a devasting factor for rural population due to change in climate and land management.

Regarding the overall importance of locust impact all over the world, we propose to generate a standardized database for all locust pest species with special focus on species-relevant conditions. Such a database could support areal planning, includes all necessary information and may be an important backup for urgent interaction independent in the case that ground monitoring and management is missing or restricted. The variability of different climatic, edaphic and landscape parameters influence the population dynamics even of adjacent local CIT population in their long-term dynamics (Sergeev, 2021; Sergeev and Van'kova, 2008). Therefore, additional holistic research focusing on spatial and temporal variability of all parameters under consideration of local population dynamics within the habitats is necessary. Geospatial and remote sensing data provide an ideal base to conduct more complex spatial distribution modelling and contribute to further understanding of population upsurges which lead to locust outbreaks.

6.6 Conclusions

Locust management is a multi-disciplinary challenge and requires the understanding and handling of diverse information and datasets. Decision support systems for locust management at various levels using the interpretation of available geospatial and remote sensing data are still lacking for many dangerous locust pests. In this study, we introduce a concept towards a comprehensive usage of geospatial and remote sensing data. The concept simplifies complex datasets with different spatial and temporal characteristics into reasonable spatial units which can be used by stakeholders to improve monitoring, control efficiency and contribute to more sustainable planning practices. Furthermore, being aware of areas of higher or lower risk and being able to predict hatching and outbreak timing can contribute to timely sustainable control and minimize the “over-usage” of pesticides in large areas. The presented use case for Italian locusts in the Pavlodar region shows that spatial data can effectively be integrated for practical applications of locust management.

Furthermore, the application of geospatial and remote sensing datasets within a simplified h3-system may close the discrepancy between users experience and available information. Information within the h3-system can be easily exploited by locust experts without the need for additional pre-processing steps and detailed knowledge of data formats and specifications. Meteorological variables were calculated in standardized hexagons, containing CIT-relevant climatic and land cover characteristics and can be utilized for expert-defined rule-sets and provide additional information for monitoring and areal planning. This can contribute to preventive locust management by prioritizing areas for locust control measurements based on historical and ongoing favorable conditions as well as by predicting hatching and outbreak times.

The application of geoscientific data provides additional opportunities which can be used independently from funding, political programs, or security situation. Especially, because locusts can inhabit vast areas during favorable conditions, it is vital to monitor and map areas of potential risk for all locust pests around the world in collaboration with regional locust experts. Therefore, the application and development of remote sensing and geospatial datasets regarding different locust species do not only support locust management but also provide a back-up database for periods with less funding or socio-political conflicts. Nevertheless, operating field officers will remain the most crucial factor.

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CHAPTER 7

7 Synthesis and outlook

7.1 Overall conclusions

Plagues and outbreaks of locusts have caused famine, harvest failures and negative impacts on grazing livestock ever since mankind became sedentary. Due to significant economic and social consequences of plagues and outbreaks, national and international preventive locust management and regular ground surveillance activities have been established to control locust population for many dangerous species around the world (Lecoq and Cease, 2022). In some cases, satellite data and remote sensing-based approaches are used operationally to map and monitor locust habitats and forecast locust upsurges and possible outbreaks.

In this context, the goal of this dissertation was to investigate current remote sensing applications for locust management and research as well as the development of new approaches for three dangerous locust species. In a first step, the conducted literature review highlighted that there are only few studies and methods exploiting remote sensing data for locust pests, besides of the desert locust, Australian plague locust and migratory locust. Second, this thesis presented modelling approaches utilizing remote sensing and geospatial datasets for Italian locust, Moroccan locust, and desert locust which are three species with high capability to damage crops, pasture and natural vegetation on large territories. The combination of different datasets was used to extract habitat suitability at higher spatial detail and provide spatial information about areas where successful locust breeding can be expected. Third, based on the 2022 outbreak of the Moroccan locust in Sardinia (Italy), the potential of Sentinel-2 data to provide fast and valuable information was demonstrated. A clear relation between land surface changes and breeding locations was quantified. Finally, the usage of the standardized h3 polygon system was examined as a tool to simplify different geospatial datasets thus contributing to straightforward applications within locust management. Furthermore, both presented case studies of the Italian locust and the Moroccan locust demonstrate that breeding locations were situated on previously transformed land for either pasture or agriculture. Therefore, continuous monitoring based on remote sensing data can be a valuable asset to characterize areas for possible population upsurges in the present and in the future.

The main objectives of this dissertation, formulated in Chapter 1, are discussed in detail in Chapter 3 to 6. In addition, the following paragraphs provide a short summary in relation to each objective and formulated research questions.

Objective 1: "Conduct a comprehensive review on international studies which have used remote sensing data in the context of locust distribution, monitoring and forecast"

Research Questions 1:

- Which locust species have been investigated by means of remote sensing applications?
- Where were remote sensing-based analyses for locust management and research conducted?
- Which satellite sensor types were used for locust management and research studies?
- What kind of remote sensing-based variables and indices were applied for locust management and research studies?
- What time periods are covered by remote sensing-based locust management and research studies?
- What are the thematical foci of the existing studies?

In Chapter 3, a comprehensive review about the role of remote sensing for locust management and research is presented. The review reveals that based on a total of 110 publications on remote sensing application for destructive locust/grasshopper pest species, the majority is conducted for desert locust (33%), the migratory locust (27%) and the Australian plague locust (14%). All other species such as brown locust (4%), the Central and South American locusts (1%), the Italian locust (5%), the Moroccan locust (1%) or the red locust (1%) received comparatively very little attention. In this regard, the regions of interest are correlated with the species' presence and its distribution of natural habitats focusing on China (24%), Australia (14%) and Mauritania (11%) with almost no studies for other regions which are prone to locust outbreaks: Arabian Peninsula (none), the Middle East and Pakistan (none), India (1%), South-East Asia (1%), North and South America (2%) and Russia (2%). Also, Central Asia, Caucasus, Europe, South-East Asia and South America and their species have been rarely examined applying remote sensing data and methods.

Most of remote sensing data applications focused on optical sensors (57%), radar (6%) and TIR (3%), where radar and TIR were mostly part of fused or combined applications with other sensors: optical/radar (10%), optical/radar/TIR (5%), radar/TIR (5%), optical/TIR (3%). Applications based on VHR data were still not existing. In terms of variables, a high ratio of studies is based on vegetation and land cover characteristics such as NDVI, land cover information, LAI or fCover (39%, 13%, 5%, 4%), referring to the importance of vegetation as a key parameter affecting population density and phase change of locusts. Soil moisture studies (9%) have received higher attention due to recent developments in technology and open source radar data availability.

Another important aspect of the review was the categorization of applications which revealed the following foci: habitat monitoring (39%), followed by habitat mapping (25%), outbreak/hatching prediction (17%) and general review publications (10%) with very few test studies on how vegetation damage caused by locust can be quantified.

Furthermore, the analyses of origin of reviewed studies indicates that, with the exception of China and Australia, most research was conducted outside the regions prone to locust outbreaks. Studies based on long-term data and large regions (e.g. entire habitats of a certain species) are still highly required. This is necessary to improve our understanding of temporal dynamics of locust outbreaks, the relation to large scale climatology, as well as our understanding about spatial distribution of different species.

Objective 2: "Use different remote sensing and geospatial datasets to demonstrate the advantage of data combination and higher-resolution datasets such as Sentinel-2"

Research Questions 2:

- How can unique locust species characteristics be included in modelling approaches?
- What kind of up-to-date climate and geospatial datasets can be used to conduct Ecological Niche Modelling (ENM) and Habitat Suitability Index (HSI) modelling for selected locust species?
- How can suitable conditions for locust breeding and potential population upsurge be better differentiated?
- What are the advantages of improving spatial resolution of modelled results?

The Italian locust, Moroccan locust, and desert locust within their vast habitats are dangerous species which can outbreak and lead to damage in agriculture and pasture during favorable conditions. In this study, ENM and HSI models were combined to improve results regarding the localization of the spatial distribution of potentially highly suitable breeding areas. Relevant ecological parameters favoring locust presence and population increase were derived from literature review and expert knowledge to account for specific species preferences. Moreover, human interaction and actual land surface characteristics play a crucial role for locust outbreaks. Therefore, modelling based on climatic and edaphic variables alone provides only information about the ecological niche of a species without considering actual changes and current state of the landscape. Within this objective, a HSI based method was presented which includes the actual state of the land cover to further narrow suitable breeding areas. Results highlight high potential to enable a better prioritization and spatial focus to support rapid field monitoring, and controlling outbreaks. The AUC measure of the HSI maps for 2019 showed good prediction performance of 0.747 for CIT, 0.850 for DMA and 0.801 for desert locust. The areas of “very high breeding suitability” (0.8-1.0) and “high breeding suitability” (0.6-0.8) for Italian locust in Pavlodar oblast were 4% (4,970 km²) and 61% (75,912 km²), for Moroccan locust in Turkistan oblast 16% (18,765 km²) and 7% (8,535 km²) and for desert locust in Awash river basin 3% (3,045 km²) and 37% (39,733 km²). Compared to ENM alone, the area characterized by “very high breeding suitability” and “high breeding suitability” reduced by 22% (27,633 km²), 11% (12,372 km²) and 23% (24,246 km²) respectively, which could enable prioritizing and adjusting areas for locust management activities progressively on yearly basis.

Objective 3: “Analyze the recent Moroccan locust outbreak in Sardinia (Italy) from the perspective of remote sensing based on up-to-date land cover characteristics with focus on favorable conditions for this species”

Research Questions 3:

- What are the relations between recent Moroccan locust outbreak in Sardinia and land cover characteristics derived from Sentinel-2 data?
- What kind of land surface was preferred by Moroccan locust for breeding during the outbreak?
- How can remote sensing analyses contribute to an early warning system and decision support to minimize higher risk concerning this agricultural pest?

Within this objective, the relation between different Moroccan locust life phases on the one hand and current land management as well as previous activities on the other hand was quantified based on Sentinel-2 data. The analysis shows that 43% of breeding locations during the 2022 outbreak were found on land which was previously used for agricultural purposes (abandoned, fallow or previously tilled land). Additional 23% were located on cropland but in vicinity (500 m) to abandoned, fallow or untilled land. The vicinity consideration accounts for possible displacement after hatching as well as inaccuracies of land cover classification. Furthermore, it was found that the majority of breeding locations, detected on abandoned, fallow or untilled land, were occupied by active agriculture until 2020. This indicates that DMA has found favorable conditions and invaded this territory immediately after the areas were not used intensively any more. Considering the transformation of abandoned, fallow or untilled land, the majority of locations are found on land classified as sparse vegetation/grassland (97%).

It total, it was demonstrated that remote sensing analyses using Sentinel-2 data can provide valuable up-to-date information for DMA upsurges. Such information can contribute to an early warning system and assist decision support to localize regions of higher risk concerning this agricultural pest.

Objective 4: “Demonstrate an application case for locust management, based on expert rule set exploiting remote sensing and geoscientific datasets”

Research Questions 4:

- How can different types of geospatial and remote sensing datasets be simplified for a straightforward spatial analysis?
- How can expert rules, applied in practice, be implemented to exploit geospatial and remote sensing datasets?
- What kind of practical locust management tasks can be conducted by such spatial applications?

Since locust management is a multi-disciplinary challenge, it requires an understanding and handling of different environmental and meteorological parameters. However, decision support systems for locust management at various levels, using the interpretation of available geospatial and remote sensing data, are still missing for many dangerous locust pests. The introduced concept based on a hexagonal h3-system simplifies complex datasets, characterized by their different spatial and temporal features, into reasonable spatial units. Those units can then be used by stakeholders to contribute to an improved monitoring, more efficient control mechanisms, and to environmentally more sustainable planning practices. The presented examples demonstrate how areas of higher or lower risk can be derived from expert rule sets. Furthermore, the concept was used to predict hatching timing for the entire study region using expert based protocols. The advantage of spatial application can contribute to a timely sustainable control as well as minimize the “over-usage” of pesticides in large areas. Furthermore, by using up-to-date Sentinel-2 time-series analyses, the recent state of land cover with a focus on abandoned, fallow or not tilled land was derived also for this species. Most breeding locations of CIT between 2016-2020 were found in areas which became abandoned or fallow during the period 2016-2020 (62%) and 2011-2015 (15%). This underlines the hypothesis that annual changes in land use and land cover directly influence locust population’s dynamics because of changes in nutrient availabilities.

7.2 Future challenges and opportunities

Highly migratory agricultural pests such as locust outbreaks will still occur in the future in many regions of the world. The key element for taking future actions is to understand and quantify the impact of climate and environmental changes on locust upsurges in order to protect rural livelihoods and food security (FAO, 2021a). With a global growing population, preventive locust management and sustainable control measurements of outbreaks all over the world will become even more important. Remote sensing applications are an essential part of preventive locust management and locust research for some dangerous locust species. Nevertheless, there is still a lack of applications and spatial information for various other major locust pests.

Firstly, the potential of remote sensing datasets to further improve preventive locust management and contribute to locust research can only be exploited by a close expert collaboration and knowledge exchange. Extensive knowledge on the ecology and biology of considered species and their habitats will be a key factor to keep damages as low as possible. Therefore, the development of databases focusing on species-specific parameters is necessary to properly utilize remote sensing data archives and new satellite datasets. Databases for all dangerous locust and agricultural pests should be publicly available to encourage further research, method development, education and capacity development. These may include historical field data, control operations and relevant environmental parameters originating from remote sensing and geospatial datasets. This would promote standardized applications for longer time periods and large-scale studies of entire habitats resulting into comprehensive understanding of natural and human interactions and their influences on locust population density and outbreaks. However, the availability and quality of field data (e.g., on locust life cycle stages, phases, density) is critical to derive meaningful results using existing technology and digital datasets. For example, the Global Locust Initiative (GLI) at the Arizona State University (Arizona State University, 2022), the FAO Desert Locust Hub (FAO, 2022) and FAO Locust Watch (FAO, 2021b) already provide comprehensive resources, information and data. Such initiatives have to be further maintained, improved and extended to all relevant regions and locusts pests. However, Lecoq and Cease (2022) reported that locust related research and funding undergo ups and downs with each major outbreak event. The main problem is that once outbreaks are under control, the funding and overall public interest reduce. This can lead to higher vulnerability and less sustainable measurements in terms of management, capacity development, and adaptation to technological progress, particularly regarding digital image analyses, remote sensing and GIS applications. In some cases, a re-establishment of preventive management as well as updates on research are required when susceptible countries have not suffered locust outbreaks for a long time (Trumper et al., 2022). In such cases remote sensing data and methods can then support such re-establishing measures and provide valuable spatial information.

A second future opportunity is the applicability of current open-source datasets to support large-scale areal management. This can be of crucial significance in the event of any unforeseen collapse in regular locust management (e.g., lack of funding, armed conflicts, security, inaccessibility). During geo-politically and financially critical situations, remote sensing approaches could additionally contribute to locust management. Principally, the aspect of human interaction to create or destroy locust habitats is dominant as both conflicting elements influence the abundance of many locust species (Latchininsky, 1998; Sergeev, 2021; Showler and Lecoq, 2021). Additionally, climate change is going to affect the habitats, distribution and behavior of locusts as well as the number and intensity of outbreaks (Meynard et al., 2020; Wang et al., 2019; Youngblood et al., 2022). This is because future climate will bring more droughts and more intense precipitation events (Balting et al., 2021; IPCC, 2019), both driving factors for outbreaks of many locust species in semi-arid and arid regions. Therefore, there is an urgent need for further research on how climate and global change will impact locust outbreaks (Kapuka and Hlásny, 2021). Consequently, with the areal changes of habitats, geospatial applications will be highly useful for all dangerous locust species (Latchininsky, 2013).

Thirdly, Cheke et al. (2020) discussed that solar activity and ocean oscillation systems can be used to predict locust abundance and therefore forecast possible locust upsurges. Applications towards spatio-temporal variability of weather patterns, together with related changes of relevant ecological variables which are ruled by such large-scale events and their practical implementation for preventive locust management, must be explored.

Finally, future activities should investigate the practical implementation of datasets with higher spatial and temporal resolution for locust management and research. About 15 years ago, remote sensing approaches were based on analyzing single images. For example, one Landsat scene provided enough material for several studies. Nowadays, satellite data archives cover more than 40 years of Earth history and data of new EO sensors are open to public and can be analyzed with cloud-based platforms highly efficient and at relatively modest costs (Gorelick et al., 2017). This era of ‘remote sensing big data’ (Xu et al., 2022) can be explored as strategic asset for preventive locust management and locust research including deep learning data analyses and modelling approaches based on improved and up-to-date datasets. In the future, similar development might enable full exploitation of VHR datasets of commercial or military satellites (less than 1 m spatial resolution) as well as UAV datasets with advanced deep learning methods. In this regard, remote sensing approaches will not only contribute to monitoring the environmental conditions within locust habitats but also allow actual detection of high insect density, typically for locust groups and bands during gregarious phase. Automatic, effective and accurate detection methods will have to be developed and implemented into modern locust management. Additional approaches exploiting hyperspectral remote sensing datasets and multi-satellite data fusion focusing on more detailed vegetation type classification, as well as soil moisture and soil temperature estimates at higher spatial and temporal resolution (Piou et al., 2019), could provide new insights.

Last but not least, the consumption of locusts, especially during outbreaks and plagues, is common in different regions and cultures (Kietzka et al., 2021; van Huis, 2021). Therefore, harvesting edible locusts can contribute to food security and also used as an environmentally sustainable control strategy to avoid chemical treatments (Kietzka et al., 2021). In this regard, accurate spatial and temporal information on locations with higher locust densities will be crucial to progress with such strategies. Here again, remote sensing-based datasets, especially VHR and UAV data, and Insect-Monitoring Radars (IMR) (Drake and Wang, 2013), can support such activities.

To tackle the above-mentioned challenges and opportunities, and to minimize both the damage to rural livelihoods and the usage of insecticides, there is an urgent need to further develop remote sensing-based approaches for each dangerous locust pest. In the context of the recent global pandemic, regional military conflicts, wars, political or economic instability, and in combination with climate change, one can assume that such crises will also have a major impact on different locust types and lead to further outbreaks. The intensity of these future outbreaks will partially depend on the availability and quality of spatial information and resources utilizing it for effective control measurements.

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Statement of authorship

I hereby certify that I have authored this Dissertation entitled "Remote Sensing Applications to Support Locust Management and Research" independently and without undue assistance from third parties. No other than the resources and references indicated in this thesis have been used. The work has not previously been presented in the same or a similar format to another examination body in Germany or abroad. There has been no withdrawal of any academic degree. I am aware that violations of this declaration may lead to subsequent withdrawal of the degree.

I confirm that I acknowledge the doctoral regulations of the Faculty of Mathematics and Natural Sciences of Kiel University.

Augsburg, September 2022

Igor Klein