Detect-alert-deter system for enhanced biosecurity and risk assessment

by Michael Atzeni, John Muehlebach, Darren Fielder and David Mayer

September 2020

AgriFutures® Chicken Meat

Detect-alert-deter system for enhanced biosecurity and risk assessment

by Michael Atzeni, John Muehlebach, Darren Fielder and David Mayer

September 2020

AgriFutures Australia Publication No. 20-089
AgriFutures Australia Project No. PRJ-010264

ISBN 978-1-76053-118-8

Detect-alert-deter system for enhanced AI biosecurity and risk assessment

Publication No. 20-089

Project No. PRJ-010264

Researcher contact details

Name: Michael Atzeni
Address: 203 Tor St, Toowoomba QLD 4350

Phone: 07 4529 4188
Email: Michael.atzeni@daf.qld.gov.au

In submitting this report, the researcher has agreed to AgriFutures Australia publishing this material in its edited form.

AgriFutures Australia contact details

Building 007, Tooma Way
Charles Sturt University
Locked Bag 588
Wagga Wagga NSW 2650

02 6923 6900
info@agrifutures.com.au
www.agrifutures.com.au

Electronically published by AgriFutures Australia at www.agrifutures.com.au in September 2020.

AgriFutures Australia is the new trading name for Rural Industries Research & Development Corporation (RIRDC), a statutory authority of the Federal Government established by the *Primary Industries Research and Development Act 1989*.

Foreword

High pathogenicity avian influenza (HPAI) outbreaks have occurred in conventional and free-range poultry operations worldwide, exposing the vulnerability of these industries. Wild birds are a leading cause of these outbreaks. Australia has experienced seven, relatively minor, HPAI outbreaks. The risk of HPAI outbreaks in Australia compared to other countries may be lower due to differences in migratory patterns of wild birds and smarter wildlife biosecurity programs.

This project developed a prototype of a machine vision-based surveillance system to enhance wildlife biosecurity by automatically detecting and deterring target wildlife. It was programmed to recognise and target ducks, which are avian influenza (AI) reservoirs and a potential biosecurity risk. Other species may also be reservoir or bridge species that spread AI, and therefore seasonal surveys of wild birds on and around meat chicken farms were undertaken as wild bird migration patterns vary for wild birds at different times of the year.

This research has shown that machine vision technology has a role in reducing the risk of AI transmission from wild birds to commercial poultry, and improving on-farm biosecurity, especially in free-range systems. With further development, farmers can be alerted to specific, on-farm risks and respond with appropriate deterrent strategies that may be activated automatically. We foresee that this 'detect-alert-deter' strategy will reduce the odds of AI outbreaks by preventing wild birds from using farms for food, shelter and breeding. Additionally, records of detection events logged by the machine vision system may also be useful for site-specific risk assessment and management purposes.

This project was funded through the AgriFutures Chicken Meat Program, and Queensland Government funding through the Department of Agriculture and Fisheries.

This report from the AgriFutures Chicken Meat Program adds to AgriFutures Australia's diverse range of research publications. It forms part of our 'growing profitability' arena, which aims to enhance the profitability and sustainability of our levied rural industries. For the Australian chicken meat industry, RD&E supports the industry to provide quality wholesome food to the nation. Most of AgriFutures Australia's publications are available for viewing, free downloading or purchasing online at: www.agrifutures.com.au.

Mr John Smith

General Manager, Research
AgriFutures Australia

Acknowledgments

The research team wishes to acknowledge the cooperation of the chicken meat industry for allowing us to use farms for this research. We thank the managers and staff of the farms for their cooperation, support and hospitality. It was greatly appreciated.

Abbreviations

AI	avian influenza
CNN	convolutional neural network
DAD	detect and deter system
DAR	detection and ranging technology (for example, radar and LIDAR)
LPAI	low pathogenicity avian influenza
HPAI	high pathogenicity avian influenza
PTZ	pan-tilt-zoom: a mounting used for a camera
RCNN	regional CNN (convolutional neural network)

Contents

Tables

Figures

Executive summary

This report describes a series of research activities that were aimed at assessing and reducing risks associated with the transmission of diseases, especially avian influenza (AI), from wild birds to farmed poultry. Research activities included:

- Developing a machine vision-based surveillance system to automatically detect, identify and record target species (Pacific Black Duck, Grey Teal and Australian Wood Duck for the purposes of this research) around poultry houses and nearby farm water storage dams.

- Durveying wild bird presence around meat chicken farms across south-eastern Queensland.

- Developing a conceptual dynamic risk assessment model.

The machine vision system was designed to be able to automatically survey wild bird activity, and use collected data to assess the risk of transmitting disease agents to the commercial flock, alert the farmer to the risk, and activate targeted deterrent strategies to reduce presence of the birds while avoiding habituation to the deterrents. (Habituation is a term used to describe the reduced effectiveness of deterrents due to a reduction in the innate response of the birds. It is often associated with frequent, repeated use of a deterrent.)

This report aims to inform integrators and industry leaders. It is ultimately their decision to set the level of biosecurity on their meat chicken farms, with some farms posing a greater risk than others. This report is also targeted at researchers conducting machine vision and machine learning across a range of endeavours to support ongoing development of this technology.

Background

High pathogenicity avian influenza (HPAI) outbreaks, caused by migratory wild birds, have seriously affected poultry industries in Africa, Europe, Asia and North America over the last two decades. The Australian poultry industries have experienced seven, relatively minor, outbreaks of HPAI, but the risk is ever-present.

The Australian chicken meat industry has invested in research to identify risk factors and to assess the risks associated with AI and other wildlife-borne diseases that can infect commercial flocks. The industry has also invested in a review of waterbird-deterrent strategies to identify cost-effective ways to reduce the risk of contact between AI maintenance species and commercial poultry flocks. Building on previous research, this research focuses on developing a system that can help to assess and reduce the risks associated with wild birds on individual farms.

Aims/objectives

The aim/objectives of this research were to:

- Identify suitable optical and microwave detection and ranging (DAR) systems for 24/7 detection of wildlife activity in and around poultry production facilities.

- Detect and discriminate waterfowl in flight, on water, and on ground, using DAR data.

- Quantify the reliability of DAR data by ground-truthing, radar and other data.

- Quantify bird activity in a poultry production area using DAR data.

- Quantify short- and long-term efficacy of selected deterrent strategies using DAR data.

- Record seasonal bird species composition data, and their behaviour, in and around production areas on representative south-eastern Queensland meat chicken farms.
- Automate the deterrent response from a detection event.
- Develop a dynamic risk-assessment model that uses DAR detection data.
- Demonstrate use of robots and UAVs as mobile deterrents.

Methods used

Research activities were separated into three streams.

1. Surveying wild bird presence, behaviour, and interaction with meat chickens on commercial meat chicken farms. Surveys included manual surveys and camera-traps methods to establish the full range of species involved and to assess daily and seasonal trends.
2. Developing a DAR system to detect wild birds, determine the type, and decide whether it should be deterred. This started with a review of DAR systems, including radar, LIDAR and optical techniques. Due to the limitations identified with using radar and LIDAR systems on poultry farms, optical DAR was selected, which led to the development of a machine vision-based system. Software and hardware development focused on a solar-powered, internet-connected, remotely controlled surveillance system that could scan a large area (e.g. around a dam), detect birds, and identify target species it had been trained to recognise. These included three species considered to pose an AI risk (Pacific Black Duck, Grey Teal and Australian Wood Duck). The system was designed to record bird activity by species and abundance, and to activate deterrent strategies in a way that would minimise habituation.
3. Developing a dynamic risk assessment model that incorporated ecological and environmental data, bird data from the detection system, and a farm dam water-balance model.

Results/key findings

- Over 140 species of wild birds were observed on or near poultry farms during camera-trap and visual surveys at 10 farms, totalling over 12,000 individual bird counts.
- We compiled a working list of ‘high-risk’ and ‘medium-risk’ reservoir and bridge species (species that could transmit infectious agents but not actually be infected) for AI maintenance and transmission based on wild bird ecology, observed behaviours, and available AI prevalence data.
- Radar- and LIDAR-based detection systems were found to be unsuitable for identifying species, collecting survey data for on-farm risk assessments, and triggering targeted deterrence of high-risk wild bird species (the species suspected of posing a disease transmission risk to farmed poultry).
- A prototype machine vision-based bird detection and management system was developed and tested at a local, privately owned dam before being deployed to a meat chicken farm. The solar-powered, Wi-Fi-connected system incorporated a pan-tilt-zoom surveillance camera and customised image processing and classification software to automatically detect birds and recognise target species.
- Automating the cropping of bird images from the system’s video data was found to be an efficient way to collect sufficient training data for developing classifiers for target species using artificial neural network techniques.

- Robust classifiers for three target species (Pacific Black Duck, Grey Teal and Australian Wood Duck) were developed using the *masked regional convolutional neural network* approach.

- We investigated a range of visual, light, and acoustic deterrents.

- The machine vision system recorded events, including all bird sightings, species classification information, and deterrent activation. This information was used for evaluating its reliability and efficacy.

- A conceptual dynamic risk assessment model has been developed (and partially programmed) to bring together ecological, meteorological, machine vision system, and wild bird AI prevalence data.

Implications for relevant stakeholders

- Assessing the risk of AI infection on meat chicken farms requires information about the prevalence of AI in wild birds (especially waterfowl), and the interaction and vectors between these wild birds and meat chicken flocks. The machine vision system developed in this project could potentially collect new information about the presence of wild birds and interactions with the flock.

- Our wild bird surveys used a combination of camera-trap and manual methods to show that many species are present on poultry farms, especially around farm dams, feed silos and range areas.

- Specific conditions or events observed during this project seemed to increase the presence of wild birds and their interaction with the chickens. Some of these included feed spills, presence of water around poultry houses from ineffective drainage, and occurrence of regional droughts that increases the attractiveness of meat chicken farms to wild birds as a source of food, surface water and shelter.

- Machine vision systems, which can involve multiple cameras covering a broad land area, potentially provide a non-invasive alternative to on-farm wild bird surveying. Compared to camera-traps, machine vision systems can cover a broader area and reduce the labour needed to sort through images. Machine vision software could also be used to improve camera-trap image processing.

- The long-term efficacy of different types of wild bird deterrents is yet to be fully assessed. However, targeted deterrence with a machine vision system is likely to be more cost-effective than traditional methods, such as bird netting, pond covers and other habitat modification. Targeted deterrence is also more likely to remain effective for longer than traditional methods, such as gas canons, flashing lights and visual deterrents, to which wild birds quickly habituate.

Recommendations

- Support more bird surveys in other meat chicken production areas of Australia to establish differences in species assemblages and associated AI transmission risks. Surveys should be carried out using traditional camera-trap and manual methods. Free-range farms should be the focus of future surveys.

- Support targeted AI surveillance of under-studied reservoir and potential bridge species to improve understanding of AI ecology and epidemiology in Australia.

- Support development of a calculator to cost ‘whole-of-farm’ biosecurity surveillance systems that incorporate machine vision capabilities to monitor and manage wild animal activity in range areas and around poultry houses, including silos and surface waters.

- Expand the capability of the machine vision system to classify other potential mechanical vectors for disease transmission, such as rodents, foxes, dogs, cats, wallabies, or kangaroos.

- Expand the capability of the machine vision system for poultry RD&E purposes. One potential use may be to replace RFID technology for monitoring range area usage and meat chicken behaviours.

- Develop education material and software (or mobile applications) to help farmers:

- Identify wild birds on their farms by species, to help with assessing their AI infection risk.

- Understand the factors that may increase AI risk on their farm, especially due to changing circumstances such as drought.

- Develop strategies to change wild bird behaviour to reduce the risk of AI transmission.

- Support continued development of the AI risk assessment model to enable automatic data input from the machine vision system as well as other inputs, including local weather, rainfall data, and water levels for farm and surrounding dams and waterways.

- Support testing and development of effective wild bird deterrent strategies, including autonomous mobile deterrents, using the current machine vision detection, and ranging system.

Introduction

Overview of this report

The central theme of this report is that risk of avian influenza (AI) outbreaks on commercial meat chicken farms can be reduced by enhancing on-farm biosecurity and risk assessment with technology. Technology may be useful for automatically detecting wild birds, recognising the species considered a risk, and deterring them or preventing their unwanted behaviour. The importance of AI and reasons for focusing on it in this project are introduced in the following sections of this report.

This research was founded on the understanding that:

- AI ecology and epidemiology in Australian wild birds is poorly understood
- AI prevalence data for most Australian species is inadequate or non-existent
- AI prevalence in commercial meat chicken flocks is unknown.

This research aligns with chicken meat industry research priorities to 'investigate economically important endemic diseases and develop better management tools, investigate biosecurity risks and develop mitigation options and strategies'. We have focused on gaining a better understanding of the interactions between wild birds and poultry on meat chicken farms, and aimed to improve AI-related biosecurity and risk assessment modelling by demonstrating the utility of a machine vision-based detection and deterrence system.

To address this theme, research activities were divided into three activities.

1. Conducting surveys of wild birds on poultry farms in three biogeographic regions of south-eastern Queensland to determine species diversity around production facilities and farm dams. Species were ranked according to their potential contribution to on-farm AI maintenance and transmission to commercial poultry flocks.

2. Identifying, developing, applying, and evaluating a detection, ranging and deterrent system that can:

- Detect the presence of wild birds around poultry houses and farm dams.
- Classify wild birds by species, with priority being given to the most likely duck species, such as Pacific Black Duck, Grey Teal and Australian Wood Duck.
- Activate deterrents using strategies that reduce the birds becoming habituated to the deterrents (to avoid the deterrents becoming ineffective).
- Record bird activity to assess the performance of the deterrence system and produce data for inclusion in a farm-based risk assessment model.

3. Developing a dynamic risk assessment model for on-farm assessment of AI risk based on wild bird presence and behaviours.

This report provides a summary of the research activities in the project, and how the combined activities contributed to achieving the research objectives. Other documents detailing some of the activities have also been prepared. The wild bird surveying activities have been drafted into two manuscripts destined for publication in peer-reviewed journals (Atzeni et al., unpublished, 2019; Fielder et al., unpublished, 2019).

A separate ‘confidential’ report (Muehlebach and Muehlebach, 2019) detailing the development of the machine vision system has also been prepared (abstract provided in Appendix 1) that describes:

- The review of detection and ranging technologies.
- Selection of machine vision concepts and technologies.
- Development of the machine vision-based system.
- Preliminary evaluation of the performance and capabilities of the system, including trials with deterrents.

We hope that you enjoy reading this summary report and get a good appreciation for the importance of on-farm wild bird surveys and monitoring for assessing risks at the wildlife–poultry interface, and the potential that we see in machine vision technology to improve on-farm biosecurity, data collection, surveillance, and dynamic risk assessment.

Avian influenza in Australia

AI is one of the most problematic and devastating diseases for poultry industries overseas. Australia has experienced seven outbreaks of highly pathogenic AI (HPAI) (Scott et al., 2018). The need for more-informed biosecurity and risk assessment data tools is important for minimising the risk of future outbreaks.

Wild birds, particularly waterbirds, are the natural reservoir for AI viruses. In Australia, the Avian Influenza Wild Bird Surveillance program coordinates AI surveillance of wild birds and waterfowl (https://wildlifehealthaustralia.com.au/programsprojects/wildbirdsurveillance.aspx). Minimising the risks of disease transmission from wild birds to farmed poultry is a primary objective of poultry production-focused biosecurity manuals (ACMF, 2010; DAFF, 2009). These manuals explicitly list wild birds as a major vector for disease and pathogen transmission. The manuals provide guidance on ways to reduce disease transmission risks associated with wild birds, including:

- Limiting access of wild birds to poultry production areas
- Designing and maintaining poultry housing to prevent entry of wild birds
- Selecting trees and shrubs to minimise wild bird attraction
- Restricting access of wild birds to feed systems
- Cleaning up feed spills without delay to prevent wild birds congregating
- Eliminating or reducing contamination of surface water (that is supplied to poultry for drinking or cooling), especially by faeces from wild birds
- For free range farms, taking steps and documenting the measures taken to minimise the congregation of waterfowl and general impacts of wild birds.

On many poultry farms, waterbirds are attracted by food, resources, and dams on or near the farm. However, predicting and managing the AI risk posed by wild birds on any given farm is challenging because of a lack of AI prevalence data and unpredictable movements of nomadic and endemic waterbirds that respond to Australia’s erratic rainfall and flooding events. This is in contrast to wild birds in Asia, Europe and North America, which have far more predictable migration patterns.

Various native species use habitat, shelter and food resources on Australian meat chicken farms, potentially contaminating water supplies and production facilities. Humans, farm machinery, wild birds and other wildlife could potentially transfer AI viruses in bird faeces into poultry houses or range areas. By surveying the presence of wild birds near chicken-rearing locations, and observing their behaviours and interactions with the chickens, we sought to improve understanding of AI transmission pathways and the species potentially involved.

Presence of waterfowl on meat chicken farms

Continuous presence of waterbirds on a poultry farm raises the likelihood of AI being present, and therefore increases the risk of transmission to poultry directly or indirectly. Australian waterfowl use farm dams. In fact, the value of farm dams as a habitat is largely underestimated, and they can become important refuges during drought. Hamilton et al. (2017) examined waterbird occupation of farm dams in south-eastern Australia's Murray–Darling Basin (MDB) and identified a wide range of pond parameters that could influence a bird's use of a water resource, including:

- Water depth
- Total water surface area
- Steepness of shoreline
- Fringing and emergent vegetation
- Logs/dead trees
- Agro pollutants
- Stock use
- Surrounding crop and pasture
- Visibility
- Biomass of invertebrate communities.

In Australia, studies on wild bird abundance need to consider spatial and seasonal variations due to massive year-to-year differences in environmental conditions. In particular, there can be fluctuations because of large-scale breeding events resulting from water reaching the central lakes (e.g. Lake Eyre and the Diamantina River Floodplains in the Channel Country).

In this project, we aimed to improve knowledge about wild bird diversity and activity, especially waterbirds, on commercial meat chicken farms. We also aimed to develop a dynamic risk-assessment model that considers the effects of regional drought and rainfall events on the AI risk on individual farms.

Review of deterrents

The chicken meat industry has previously reviewed waterfowl deterrents (Atzeni et al., 2016). The industry was looking for cost-effective ways to reduce the risk posed by waterfowl, particularly dabbling ducks. A large array of deterrents and control measures is available for waterfowl for other situations, but some are unsuitable for use on poultry farms because they will scare or change the behaviour of the farmed poultry, which is undesirable. There is also the perennial problem of habituation if scare tactics are not used intelligently and judiciously. The potential need for 24/7 monitoring and control of ducks for extended periods supports the case for automated detection and deterrence strategies that target specific species.

The earlier review considered a range of auditory, visual, chemical, and physical deterrents. The efficacy of each deterrent depended on the circumstances, but habituation was a problem in most cases. It was recommended that an intelligent detect-deter system be developed and used to judiciously activate deterrents to prolong their effectiveness. We aimed to develop such a system.

Automated detection and deterrence – the rise of machine vision

Automated detection and deterrence links a ‘positive’ detection trigger with a deterrent strategy (scare tactics, hazing/harassment tactics, or both). The detection component includes identification of the target bird (either as an object or, preferably, by species). Deterrents that are suitable for automation include:

- Gas guns/canons
- Bio-acoustics (e.g. alarm and distress calls)
- Pyrotechnic sounds
- Lasers and lights
- Effigies of humans and predators
- Moving/autonomous drones/robots.

The advantage of automated detection and deterrence systems is they can target and respond to unwanted behaviours immediately, e.g. a bird entering a no-go zone, to prevent ‘bad’ behaviours developing into a routine that can lead to habituation to the deterrent. The aim is to penalise bad behaviours, given that it is impossible to keep wild birds off farms.

Radar-activated deterrent systems have been developed for detecting birds in flight and used to deter waterbirds from landing on toxic tailing dams, and pest birds from horticulture and forestry. One limitation of radar is the inability to identify birds by species, which precludes it from being able to deliver species-specific deterrence strategies. For this reason, we did not investigate radar-based systems. Based on emerging growth and capability of machine vision systems, we decided to develop an intelligent and adaptable machine vision-activated deterrent system with capabilities to:

- Detect wild birds on land, water and in flight
- Classify birds by species autonomously from pictures or live-feed video streams
- Record bird detection events by species, and use changes in detection rates to measure system efficacy.

Objectives

This project had the following objectives:

- To identify suitable optical and microwave detection and ranging (DAR) systems for 24/7 detection of wildlife activity in and around poultry production facilities
- To detect and discriminate waterfowl in flight, on water, and on ground, using DAR data
- To quantify the reliability of DAR data by ground-truthing, radar and other data
- To quantify bird activity in a poultry production area using DAR data
- To quantify short- and long-term efficacy of selected deterrent strategies using DAR data
- To record seasonal bird species composition data and their behaviour in and around production areas on representative south-eastern Queensland meat chicken farms
- To automate the deterrent response from a detection event
- To develop a dynamic risk-assessment model that uses DAR detection data
- To demonstrate use of robots and UAVs as mobile deterrents.

Surveys of wild birds on poultry farms

Detailed descriptions of methodology, results and discussion from the wild bird survey have been drafted in journal manuscripts (Atzeni et al., unpublished, 2019; Fielder et al., unpublished, 2019).

Surveys of wild birds on 10 commercial meat chicken farms in southern and south-eastern Queensland used a combination of camera-trap and manual surveys. Camera-traps were used on seven of the farms where the manual surveys were undertaken. Surveys focused on areas around the poultry buildings, range areas, silos, and farm dams. The combined approach of manual and camera-trap surveys was to maximise the likelihood of capturing the overall species diversity and range of behaviours. Manual surveys had the advantage of not being limited to stationary locations, but it was not possible to monitor activity continuously at multiple locations 24 hours a day. In contrast, camera-traps were well suited to monitoring activity and determining time budgets in frequently used habitats (e.g. farm dams and feed silos), but had limited field-of-view. Selected images captured by the camera-traps, including a variety of species and demonstrated behaviours, are presented in

Appendix 2.

AI risk ranking for Australian wild birds

An AI risk classification system used in Europe (Veen et al., 2007) was adapted for Australian bird species so that species observed on meat chicken farms could be assigned an AI risk rating. This classification was based on observed behaviours that could facilitate introduction of AI on farms and transmission of AI to meat chickens. NB: However, in the absence of AI prevalence data for most Australian species, the suggested risk statuses should be regarded as **speculative**.

- ***High-risk*** classification was used for species previously confirmed as AI reservoirs, and species that visit water habitats frequently, or that have direct interaction with chickens on farms.

- ***Medium-risk*** species were considered to be possible intermediate reservoirs or bridge species that mix less frequently with high-risk species (bridge species were those that may transmit infectious agents, but not actually be infected).

- ***Low-risk*** species were considered to have little or no chance of contact with reservoir or bridge species, or infectious material.

During the surveys, more than 140 species of birds were observed (

Table 1). About 40% of the detected species were categorised as medium to high AI risk, based on their habits on-farm (e.g. entering sheds and interacting with the chickens on range areas), and assuming any of these species could become infected, until there is evidence to the contrary. This highlights the significant gap in the knowledge of AI prevalence in wild bird species in Australia, and a potential need for more surveillance activities on these species.

Water habitats (farm dams and stormwater runoff drains) attract reservoir and bridge species, including waterfowl species considered high risk, including Pacific Black Duck and Grey Teal. The range areas and silos were also found to be popular habitats for a variety of high and medium AI-risk species, including Australian Wood Ducks. Several species, including House Sparrow, Welcome Swallow and Apostlebird, were observed inside meat chicken houses.

Feed spills around silos were found to attract a number of birds and other animals (including Brush Turkeys, wallabies, goats and rodents). Accumulated bird droppings around the silos have a high likelihood of being physically transported into range areas and poultry houses by these animals or farm workers/machinery. Similarly, surface water pooling on range areas or near poultry houses due to poor drainage and water spills (from cooling and drinker systems) was found to attract some birds that normally would not be there.

Our survey observations highlighted the need to be vigilant about cleaning feed spillage, and ensuring that water drains away completely after rain or water leakages to reduce the potential risk of AI transmission from wild birds. There was an abundance of birds around farm dams, range areas, silos, and chicken houses. This observation reinforced the need to focus on these spots with our developing machine vision system to enable detection and documenting of wild birds. It also highlighted the need for deterrence systems to cover extensive areas.

Table 1 **Common names of wild bird species (alphabetical order) observed during the camera-trap and manual surveys, grouped by suggested AI risk factor.**

Suggested avian influenza risk factor				
High	**Medium**	**Low**		
Australasian Darter	Apostlebird	Australian Hobby	Golden-headed Cisticola	Sacred Kingfisher
Australasian Grebe	Australian Brush Turkey	Australian Reed Warbler	Grey Butcherbird	Scaly-breasted Lorikeet
Australasian Pipit	Australian Magpie	Bar-shouldered Dove	Grey Fantail	Scarlet Honeyeater
Australian Raven	Australian Magpie-lark	Black Falcon	Grey Shrike-thrush	Shining Bronze-Cuckoo
Australian White Ibis	Australian Pelican	Black-faced Cuckoo-shrike	Horsfield's Bronze-Cuckoo	Silvereye
Black Swan	Australian Wood Duck	Black-faced Monarch	Jacky Winter	Spangled Drongo
Black-winged Stilt	Black fronted Dotterel	Black-shouldered Kite	Leaden Flycatcher	Speckled Warbler
Cattle Egret	Black Kite	Blue-faced Honeyeater	Little Bronze-Cuckoo	Spotted Pardalote
Chestnut Teal	Black-fronted Dotterel	Brahminy Kite	Little Button-quail	Striated Pardalote
Comb-crested Jacana	Bush Stone-curlew	Brown Falcon	Little Corella	Striped Honeyeater
Darter	Dusky Moorhen	Brown Goshawk	Little Friarbird	Sulphur-crested Cockatoo
Great Egret	Eurasian Coot	Brown Honeyeater	Mistletoebird	Superb Fairy-wren
Grey Teal	Fairy Martin	Brown Quail	Nankeen Kestrel	Tawny Frogmouth
House Sparrow	Hardhead	Channel-billed Cuckoo	Noisy Friarbird	Tawny Grassbird
Latham's Snipe	Intermediate Egret	Cockatiel	Noisy Miner	Tree Martin
Little Black Cormorant	Laughing Kookaburra	Common Bronzewing	Olive-backed Oriole	Varied Sittella
Little Grebe	Nankeen Night-heron	Common Koel	Pacific Baza	Variegated Fairy-wren
Little Pied Cormorant	Pied Cormorant	Common Myna	Pale-headed Rosella	Wedge-tailed Eagle
Magpie Goose	Rainbow Bee-eater	Common Starling	Peaceful Dove	Weebill
Masked Lapwing	Royal Spoonbill	Crested Pigeon	Pheasant Coucal	White-breasted Woodswallow
Pacific Black Duck	Straw-necked Ibis	Dollarbird	Pied Butcherbird	White-browed Scrubwren
Plumed Whistling-duck	Torresian Crow	Double-barred Finch	Pied Currawong	White-plumed Honeyeater
Purple Swamphen	Whistling Kite	Eastern Osprey	Plum-headed Finch	White-throated Gerygone
Wandering Whistling-Duck	White-backed Swallow	Eastern Whipbird	Rainbow Lorikeet	White-throated Honeyeater
Welcome Swallow	White-faced Heron	Eastern Yellow Robin	Red-backed Fairy-wren	White-throated Needletail
White-bellied Sea-Eagle	White-necked Heron	Fan-tailed Cuckoo	Red-browed Finch	Yellow Thornbill
	White-winged Chough	Figbird	Red-rumped Parrot	Yellow-faced Honeyeater
	Willie Wagtail	Forest Kingfisher	Restless Flycatcher	Yellow-rumped Thornbill
	Yellow-billed Spoonbill	Galah	Rock Dove	Yellow-tailed Black-Cockatoo
		Golden Whistler	Rufous Whistler	

Machine vision system development

Detailed description of the development of the machine vision detect-alert-deter system (DAD system) has been prepared in a separate report (Muehlebach and Muehlebach, 2019) (abstract provided in

Appendix 1). We strongly emphasised the development of the DAD system because we saw it as the foundation stone to the testing of strategic deterrence strategies. The actual deterrents (lights, bio-acoustics, inflatable ‘scary man’) have been reviewed before (Atzeni et al., 2016). Effectiveness of deterrents is known to vary due to a variety of factors, including bird species, distance between birds and deterrents, experience with deterrents, and established bird behaviours. The issue with any deterrent is ‘habituation’, when birds become familiar with it and it is no longer effective. Habituation occurs more quickly when deterrents are activated indiscriminately, for example, too regularly or randomly (such as when used on a timer or when target birds may be at sufficient distance to hear or see the deterrent but not be startled by it).

The aim of our DAD system was to:

- **Target** specific bird species that are known to be reservoirs for AI, and activate deterrents only when these species are detected.
- **Prevent** wild birds from establishing undesirable behaviours, such as entering poultry houses or feeding from feed-spills under silos.
- **Disrupt** and break undesirable behaviours, where wild birds may already be visiting poultry farm dams and range areas (perceived as high-risk behaviours).

A DAD system using the visible light spectrum was found to have greater potential than existing radar systems because of the ability to identify birds by appearance, which, with training, enables classification of birds by species rather than just as an object. Training is the most essential task because it determines how reliably a target species is ‘identified’ and therefore how frequently the deterrents need to be triggered. The goal is to minimise false positives to prevent overuse and habituation. Furthermore, determining the efficacy of the system for any given species is dependent on how well it has been trained to discriminate the species in the first place.

Three species (Pacific Black Duck, Grey Teal and Australian Wood Duck, with ‘other birds’ classified as such) were classified with a high degree of confidence using a selection of open source and customised computer vision and artificial neural networking software.

A prototype DAD system (Figure 1) was solar powered, had dedicated computer hardware, used a pan-tilt-zoom (PTZ) camera that enabled it to scan a broad area, and communication hardware to enable it to send data or event logs over the internet or Wi-Fi.

Figure 1 Prototype machine vision DAD system.

Development and training of the software to recognise birds and classify them by species (Figure 2) were major components of this project. Deploying the prototype DAD system at a dam and onto a poultry farm allowed the system to be tested for ability to detect and classify birds in the field of view. The system classified chosen duck species with a high degree of accuracy when they were on the ground or in the water. The classification process was not as accurate for birds in flight because it was much harder to obtain the necessary training data for this purpose.

Figure 2 Machine vision system automatically identified the presence of birds and classified them according to species (image reproduced from Muehlebach and Muehlebach (2019)).

Detection and classification of birds by species allowed the system to record and log bird detections. In the following example (Figure 3), the machine vision system was installed near a farm dam. The PTZ camera cycled through several predetermined locations around the dam. The average number of birds observed per hour was calculated from the total count of birds detected by the machine vision system repeatedly cycling through the predetermined locations. Higher counts indicated when more birds were present.

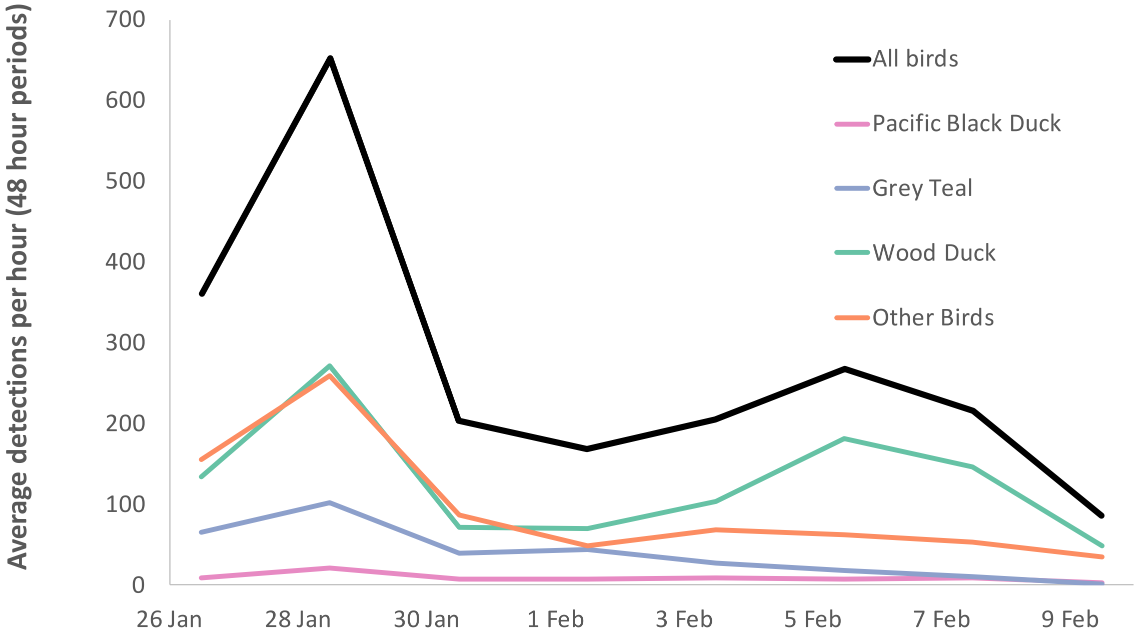


Figure 3 Time series record of average bird detections per hour at a farm dam by the machine vision system – averaging period 48 hours.

The machine vision system also provided data over shorter averaging time periods (for example, every three hours) to reveal periods within each day when bird abundance was greatest (Figure 4). In this example, we can see that the count of birds detected was dominated by Australian Wood Ducks and 'other birds'. There were much fewer detections of the Pacific Black Duck and Grey Teal, which are considered to be 'high-risk' species for AI transmission. At this dam, bird abundance was greater during the day and lower at night. This data was found to be useful for identifying behaviour patterns and determining deterrent-activation strategies.

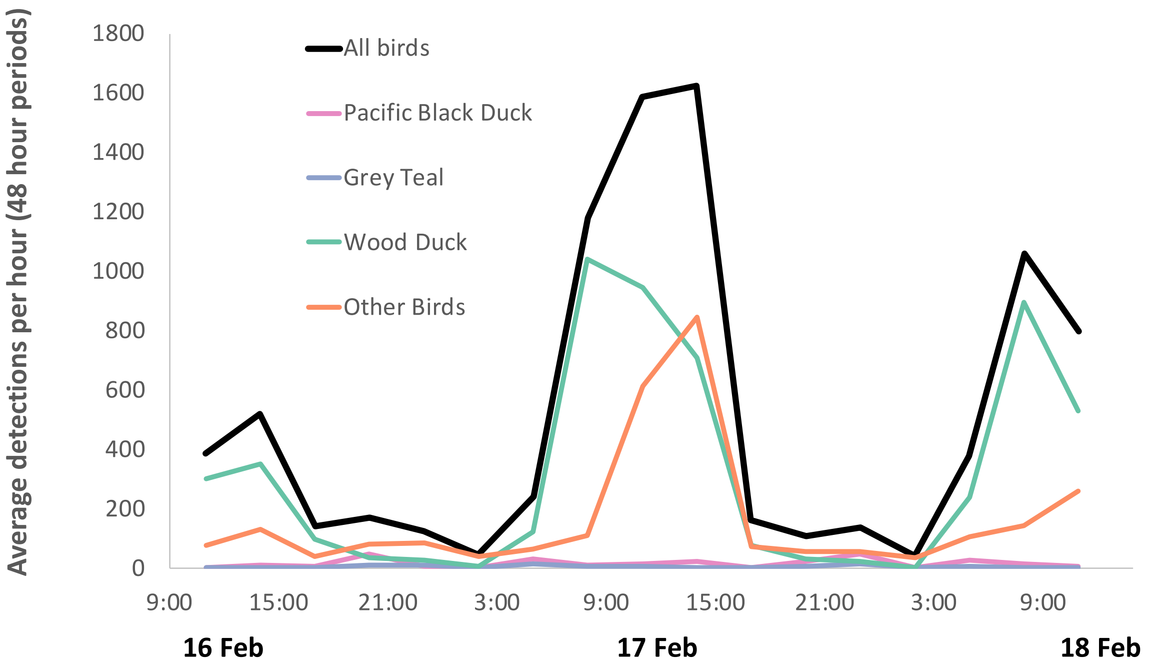


Figure 4 Time series record of average bird detections per hour at a farm dam by the machine vision system – averaging period 3 hours.

The DAD system could activate deterrents automatically, or manually by logging into the camera and remotely monitoring the scene. During efficacy trials, the manual method was used to enable observation of the birds' reaction to the deterrents. Deterrents were used sparingly because of the focus on software development for streamlining image collection and training the system to reliably recognise and classify target species. More frequent use of the deterrents would have scared the birds away and provided fewer opportunities to train the system for identifying birds and logging the detections.

Deterrents in our evaluation of the DAD system included fox lights (flashing LEDs), bio-acoustic sounds (distress calls) and an inflatable 'scary man' (similar to that used by some businesses to attract attention to their business). When we evaluated the short-term efficacy of these deterrents through observation, we found that the deterrents were ineffective at deterring waterfowl from a dam. When the deterrents were activated, birds tended to move away but returned within a period of a few minutes to several hours, and resumed their regular activity. With the static deterrents placed on the banks of the dam, birds tended to flee only to the middle of the dam where they likely felt safe. It was evident that multiple deterrents, and probably mobile deterrents, would be necessary to effectively deter birds from farm dams.

A combined deterrent, including a scary man and bio-acoustics (Figure 5), was trialled near farm silos where wild birds were feeding. Repeated activation of this deterrent (only when target birds were present) was 100% effective over a three-day period. This short-term trial demonstrated that the DAD system could be effective around poultry houses, but longer trials are necessary to understand whether or when birds become desensitised to the deterrent.

Figure 5 Bio-acoustics and inflatable man (image reproduced from Muehlebach and Muehlebach (2019)).

Development of the prototype DAD system was ambitious. Software took longer than anticipated, but was a necessary first to enable longer-term trials and automatic deterrent activation. To our knowledge, there are no other systems in the world with the capabilities of this system.

At the end of this project, we consider the prototype machine vision DAR system to be fully developed to a prototype/research level. More research and development is necessary to refine, improve and evaluate the system to:

- Conduct longer-term trials across a wider geographic area to test different deterrents
- Record bird numbers or activity on a time-scale, and present this data to users
- Streamline software with a user-friendly interface
- Improve metrics capability and diagnostics
- Develop a camera costing system that allows tailoring to individual situations
- Develop an autonomous vehicle interface to control and direct mobile deterrents.

Dynamic risk assessment model

We have developed a concept for a daily time-step dynamic risk assessment model for AI with three input components (Figure 6).

1. An individual AI risk classification of High, Medium or Low assigned to individual wild bird species, (as described above in the 'AI risk ranking for Australian wild birds' section)
2. Dynamically collected target species data from the machine vision system
3. Hydrology modelling of on-farm and remote dam storage levels to predict when regional waterways are drying up, or inland breeding events are ending, potentially influencing the appearance and residency time of waterfowl on poultry farm dams.

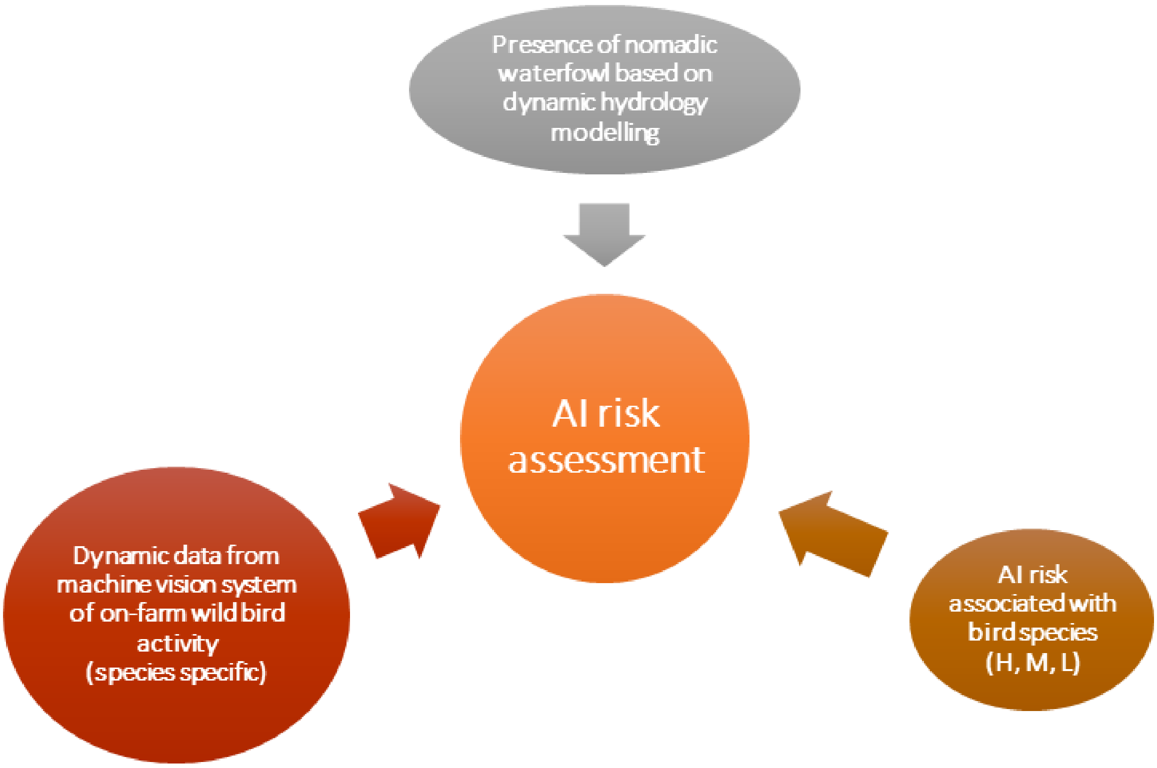


Figure 6 Conceptual dynamic risk assessment model.

The hydrology modelling approach has not previously been attempted for this purpose, but breeding and movements of Australian waterfowl are strongly influenced by droughts and floods. Pond morphology (e.g. area, depth, volume, shore length and water quality) influences bird numbers. Modelling the hydrology of dams on poultry farms and other regional surface waters will enable prediction of when birds are likely to be on poultry farm dams and why, which may in turn influence the risk and the need to be proactive in deterring them.

We investigated multiple models and found that MEDLI (DES, 2015) (Model for Effluent Disposal using Land Irrigation) had suitable functionality for hydrological modelling. It would be reasonably adaptable to include other factors we believed necessary. We conceptualised that the model would include not only hydrological factors (such as rainfall, evaporation and runoff from roofs, range areas and pavement surfaces), but also pond morphological factors and regional bird breeding event information to predict likely abundance of birds being attracted to the farm dam (Figure 7).

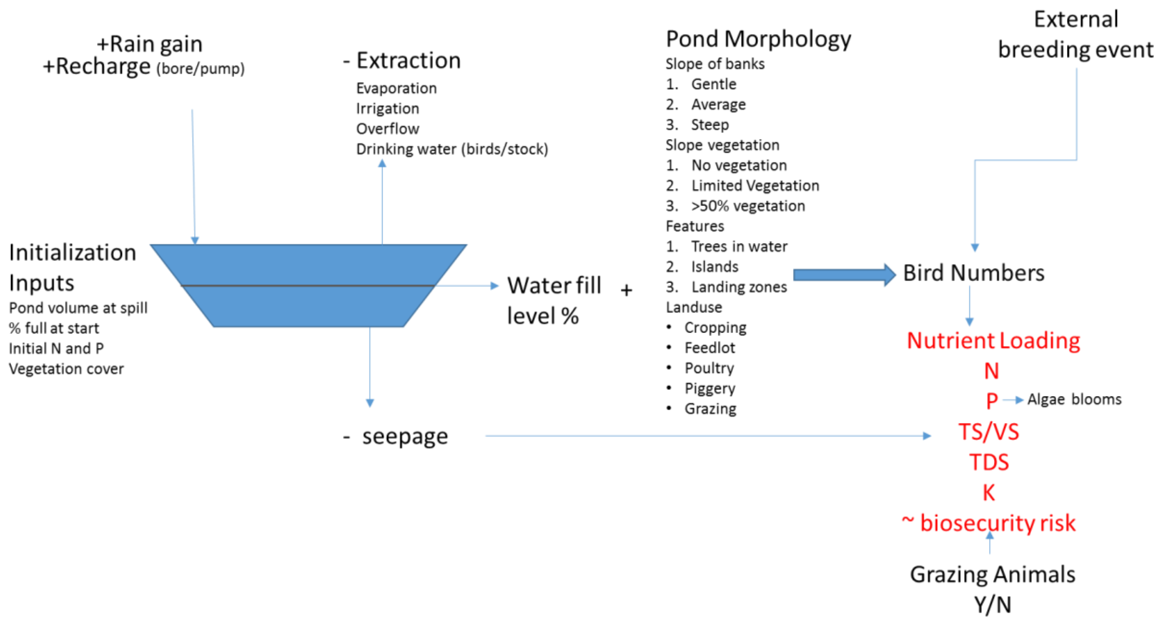


Figure 7 Schematic of a hydrology model involving waterfowl numbers/breeding potential and other morphological information to calculate the attractiveness of poultry farm dams for migrating nomadic waterfowl.

Because we strongly emphasised developing the machine vision system as a functional research tool, software development for the dynamic risk assessment model did not progress as expected. The model was partially developed and programmed to:

1. Import daily time-step meteorological data for any chosen site (SILO database).
2. Use a simple pond hydrology and catchment model.
3. Enable visualisation of periods when a farm with a permanent water storage would be attractive compared to a hypothetical farm that had only an ephemeral water storage.

With a knowledge of the lag between breeding events and the dispersal of naïve first-year waterfowl, the AI risk can be better anticipated and managed, even without the machine vision data. However, machine vision data will be necessary to verify the model’s waterbird predictions.

Conclusions

In relation to specific project objectives, the following is a summary of our achievements in this project.

To identify suitable optical and microwave detection and ranging (DAR) systems for 24/7 detection of wildlife activity in and around poultry production facilities.

We investigated a range of options that use the visible light spectrum, non-visible light, and non-optical techniques. We found that microwave- and radar-based systems had significant limitations, such as being unable to be used around buildings and being unable to differentiate birds from other objects, let alone identify them by type and species. Methods using non-visible light, e.g. thermal imaging cameras, had limited ability to differentiate birds from the surrounding environment, especially during the day, and therefore were less practical than using the visible light spectrum. We focused on developing a machine vision system using the visible light spectrum to take advantage of cost-effective security cameras, video recording hardware, and readily available open-source computer vision software.

To detect and discriminate waterfowl in flight, on water, and on ground, using DAR data.

The prototype machine vision system developed in this project was trained primarily for bird detection (but can also be used to detect other animals). It has been trained to reliably recognise and classify some common ducks found in south-eastern Queensland (Pacific Black Duck, Grey Teal and Wood Duck) when they are not in flight. The system can also detect waterfowl in flight, but species classification is less reliable (due to insufficient training data, and it is not considered necessary or practical at the species level).

To quantify the reliability of DAR data by ground-truthing, radar and other data

The prototype machine vision system included functionality to record any event when birds were detected; these recordings also served as the source data for training the system. Other software was developed to automatically crop images of birds, and file the images in folders specific to the species it has been trained to recognise. The research team reviewed all stored images to ensure they were properly classified. Misclassified images were re-used for training to improve the system. The machine vision system was trained to correctly classify images of three species of ducks—Pacific Black Duck, Grey Teal and Australian Wood Duck—with better than 99% accuracy in ideal situations, which is better than most humans could achieve.

To quantify bird activity in a poultry production area using DAR data

The prototype machine vision system was deployed to a meat chicken farm. It continually monitored and recorded wild bird activity at various pre-set camera positions (silos and dam), and it classified birds into the target species (Pacific Black Duck, Grey Teal and Australian Wood Duck) or as ‘other species’. More development is required for the system to produce integrated time-series data from its event database in formats that can then be used for dynamic risk assessment modelling.

To quantify short- and long-term efficacy of selected deterrent strategies using DAR data

The short-term efficacy of static deterrents (LED lights, bio-acoustic recordings, pop-up effigy, i.e. inflatable scary man) used singularly and in combination to scare roosting ducks at a farm dam was evaluated from manual analysis of system-captured video and data. Efficacy was specific to the deterrents used and how they were deployed. Using static deterrents for roosting waterfowl on farm dams provided only short-term change to roosting behaviours. Birds tended to move from the roost and seek sanctuary on the water, away from the ‘threat’. This behaviour indicates a second phase of harassment using mobile deterrents (such as with an unmanned boat or amphibious vehicle) is likely necessary to reinforce static deterrents at water habitats. When tested on a poultry farm at the silos, where wild birds including ibis and ducks were observed eating spilled feed, efficacy was excellent. Repeated use of the deterrent kept birds away from the silos and nearby small runoff dam for several days.

Testing the long-term efficacy of the DAR system was not possible because of operational constraints. Training of the classification system was considered to be more important for the DAR system, which required the continual presence of target species as image data, so it was not in our best interests to constantly scare them away. More research will be needed to undertake meaningful long-term trials and incorporate the trial of mobile deterrents.

To record seasonal bird species composition data and their behaviour in and around production areas on representative south-eastern Queensland meat chicken farms

Wild bird surveys were undertaken using camera-traps and manual surveys at 10 poultry farms. The surveys took in all seasons to account for the dynamic avian diversity and to identify candidate reservoir and bridge species on farms in different regions of south-eastern Queensland. Over 140 species of wild birds were observed, despite less than ideal conditions (drought) for waterbirds at some sites. Several species are known reservoirs of avian influenza (AI). These and other potential reservoir and bridge species were assigned a ‘high’, ‘medium’ or ‘low’ AI-risk status using a scoring and ranking method developed in this project. These ratings should be considered as speculative because AI prevalence data for most of these species is lacking.

To automate the deterrent response from a detection event

The prototype machine vision system automatically activated deterrents during an efficacy trial at a meat chicken farm. During development, research staff also remotely monitored and activated deterrents by logging into the networked IP camera, when birds were observed or ‘recognised’ by the system. Either capability is potentially useful in future, depending on the circumstances. Based on observations and experience, mobile deterrents are more effective than stationary ones, especially for waterbirds and large areas. Amphibious, aerial, and water-based vehicles that can controlled by the machine vision system should be investigated.

To develop a dynamic risk-assessment model that uses DAR detection data

Components of a conceptual dynamic risk-assessment model have been investigated and developed, but a working dynamic risk-assessment model has not been fully achieved because of data requirements. In this project, we have:

- Developed a scoring and rating system for assigning bird species with a ‘high’, ‘medium’ or ‘low’ AI-risk status. These ratings should be considered as speculative until they are confirmed with species-specific AI prevalence testing. Our process considers the ecology, behaviours, and species interactions (e.g. sharing range areas is higher risk than roosting in trees well away from the production area).

- Developed a machine vision system that records bird activity on the poultry farm, especially in ‘hotspots’ where close interaction can occur between the wild birds and farm chickens. In combination with the AI-risk rankings, it is conceptually possible to calculate when the risk of AI transmission is likely to be increasing or reducing.

- Proposed another component to the risk assessment model that considers site-specific weather data and water level data for the farm and surrounding region. This concept is to improve prediction of the risk associated with nomadic waterbird access to permanent water or other resources on meat chicken farms (e.g. shelter, drinking water and feed).

To demonstrate use of robots and UAVs as mobile deterrents

The primary focus of this research was developing the machine vision system to recognise and classify birds by species. Now that it is developed, it is much more likely to be able to appropriately and strategically deploy mobile deterrents. The use of robots and mobile deterrents will require more research. The feasibility of using aquatic craft controlled by the machine vision to chase waterfowl off farm dams has been investigated.

Implications

The wild bird surveys have revealed more than 140 species that use south-eastern Queensland meat chicken farms to some extent. These species include waterfowl, which are known reservoirs for AI, and various candidate bridge species for which AI prevalence data is lacking. The presence of these birds near poultry houses and farm surface water storages reinforces the need for vigilance of on-farm biosecurity practices. Mud and bird droppings around the water storages and other hotspots, such as under feed silos and water drainage channels, may be infectious. Farm biosecurity plans need to ensure that steps are taken to reduce the risk of this material being transported onto range areas and into poultry houses. These steps include controlling movements of farm staff, machinery, rodents, macropods, mud-nesting birds and grazing waterfowl. Farmers should quickly and thoroughly clean up spilled feed from under silos, and ensure that drainage channels rapidly dry to reduce their attractiveness to animals. Doing so will likely reduce opportunities for interactions between commercial chicken flocks and potential AI vectors.

In this project, we have focused on developing a machine vision system to detect bird and animal activity, recognise target species, and judiciously activate appropriate deterrents. An effective and efficient machine vision system is the foundation to delivering capabilities for autonomous on-farm wild bird monitoring and management. Machine vision is already becoming an integral part of wildlife monitoring and agricultural management. The Australian chicken meat industry's early investment in developing this technology has revealed many opportunities and raised new ideas for how to effectively and efficiently use it in a range of applications, including:

- Monitoring/surveying wild bird and animal activity on poultry farms, including poultry houses, range areas, surface water storages and feed silos.
- Activating deterrents in a targeted and strategic manner to effectively manage wild birds and animals that may be considered high risk for transmitting diseases, from farm locations where transmission to the flock may occur either directly (e.g. direct contact in range areas or insecure animal houses) or indirectly (e.g. through drinking water, feed or physical movement of infected material, such as mud or faeces).
- Monitoring usage of range areas (spatial, temporal) in research applications by training the machine vision system to classify and count meat chickens.
- Gathering evidence to support targeted AI surveillance of those species for which reliable prevalence data is required for risk assessments.

Other sectors that have expressed interest in the use of this technology include cropping, horticulture, viticulture, pest animal monitoring/control programs, aquaculture, fisheries catch monitoring, and mining. Potential uses include autonomous monitoring of trespassers, livestock, wildlife, and pest species to alert farmers to an important situation, or to activate control strategies.

The cost-benefits of implementing this technology in the poultry industry will be determined by the perceived risk of outbreaks of AI or other wildlife-borne diseases. The value of recognising and actively managing the species that create potential pathways for diseases to enter commercial flocks should not be underestimated. We suggest that machine vision data should be combined with dynamic risk assessment modelling to help farmers understand potential risks so that they can focus on maintaining and enhancing biosecurity on their farm.

The investment of research resources into the machine vision system meant that we did not thoroughly test the long-term efficacy of deterrents, but the machine vision system is now developed to a stage where it is capable of effectively classifying and targeting specific bird species. To reduce or prevent habituation, more research will be needed to evaluate the long-term efficacy of a range of visual, acoustic and light deterrents with various deployment and activation strategies.

Recommendations

We recommend more research and development to refine, improve and evaluate the machine vision, ranging/targeting and deterrent system for the poultry industry. This includes:

- Streamlining software with a user-friendly interface.
- Improving metrics capability and diagnostics to record and report wild bird abundance.
- Recording bird numbers or activity on a time-scale, and presenting this data to users.
- Conducting longer-term trials in different geographic areas and terrains to test different deterrents.
- Conducting trials without deterrents to maximise training of the classification algorithms, and demonstrating the usefulness of the bird presence data for assessing on-farm disease risks.
- Expanding the capability of the machine vision system to classify other potential mechanical vectors for disease transmission, such as rodents, foxes, dogs, cats, wallabies, and kangaroos.
- Increasing the number of species that are able to be classified to include species considered to be ‘high’ and ‘medium’ risk based on wild bird surveys and future discussions with industry, epidemiologists, virologists, and AI experts.
- Developing autonomous vehicle interface for the machine vision system to direct mobile ground- or water-based deterrents towards wild bird targets.
- Expanding the capability of the machine vision system for research activities to automatically survey spatial and temporal use of range areas, and record bird behaviour and movement within poultry houses.
- Developing a camera costing system that allows tailoring to individual situations.

To improve awareness of wild birds, AI pathways and risk assessment on farms, we recommend:

- Discussing and obtaining consensus on species considered to be high and medium risk based on the wild bird survey data by meeting with industry, epidemiologists, virologists, and AI experts
- Monitoring in all chicken meat production regions to identify the likely maintenance species and potential bridge species
- Using machine vision capabilities to monitor wild bird activity in range areas and around poultry houses, including silos and farm surface water supplies
- Developing education material and software (or mobile applications) to help farmers:
  - Identify wild birds on their farms along with their AI infection risk (which is more than simply using existing Australian bird ID apps)
  - Understand the factors that could increase AI risk on their farm, especially due to changing circumstances, such as drought
  - Develop strategies to change wild bird behaviour to reduce the risk of AI transmission
- Supporting continued development of the AI risk assessment model to enable automatic data input from the machine vision system, on-farm weather stations, and dam-level sensors.

References

1. ACMF. 2010. National Farm Biosecurity Manual for Chicken Growers, Australian Chicken Meat Federation Inc. Downloaded from http://www.chicken.org.au/page.php?id=238 on 6/11/2019.

2. Atzeni, M., Fielder, D., Thomson, B. 2016. Deterrence of wild waterfowl from poultry production areas: a critical review of current techniques and literature: PRJ-009194, AgriFutures Australia. Wagga Wagga, Australia. Downloaded from https://www.agrifutures.com.au/product/deterrence-of-wild-waterfowl-from-poultry-production-areas-a-critical-review-of-current-techniques-and-literature/ on 22/11/2018.

3. Atzeni, M.G., Fielder, D.P., Mayer, D.G., Thomson, B.G. *in preparation*, 2019. Identifying possible pathways of AI transmission by wild birds on meat chicken farms in eastern Australia, Department of Agriculture and Fisheries, Queensland Government. Toowomba.

4. DAFF. 2009. National Farm Biosecurity Manual: Poultry Production, Commonwealth Department of Agriculture, Fisheries and Forestry. Orange. Downloaded from http://www.agriculture.gov.au/pests-diseases-weeds/protect-animal-plant/bird-owners/poultry_biosecurity_manual on 6/11/2019.

5. DES. 2015. MEDLI - Version 2, Department of Environment and Science. Queenlsand, Australia, https://www.des.qld.gov.au/science/government/science-division/medli/.

6. Fielder, D.P., Atzeni, M.G., Grady, S., Mayer, D.G., Thomson, B.G. *in preparation*, 2019. Wild bird activity on poultry farms in eastern Australia with a focus on potential avian influenza carriers, Red Leaf Environmental. Toowoomba.

7. Hamilton, A.J., Conort, C., Bueno, A., Murray, C.G., Grove, J.R. 2017. Waterbird use of farm dams in south-eastern Australia: abundance and influence of biophysical and landscape characteristics. *Avian Research*, **8**(1), 2.

8. Muehlebach, J., Muehlebach, H. 2019. Development of a machine vision system to detect, classify and deter wild birds from meat chicken farms and surface water storages - CONFIDENTIAL final report.

9. Scott, A.B., Toribio, J.-A.L.M.L., Singh, M., Groves, P., Barnes, B., Glass, K., Moloney, B., Black, A., Hernandez-Jover, M. 2018. Low- and High-Pathogenic Avian Influenza H5 and H7 Spread Risk Assessment Within and Between Australian Commercial Chicken Farms. *Frontiers in Veterinary Science*, **5**(63).

10. Veen, J., Brouwer, J., Atkinson, P., Bilgin, C., Blew, J., Eksioglu, S., Hoffman, M., Nardelli, R., Spina, F., Trendi, C., Delany, S. 2007. Ornithological data relevant to the spread of Avian Influenza in Europe (phase 2): Further identification and first field assessment of Higher Risk Species, Wetlands International. Wageningen, The Netherlands. Downloaded from https://www.wetlands.org/publications/ornithological-data-relevant-to-the-spread-of-avian-influenza-in-europe-phase-2/ on 6/11/2019.

Appendix 1: Machine vision system report

‘Development of a machine vision system to detect, classify and deter wild birds from meat chicken farms and surface water storages’

Confidential final report by John Muehlebach & Heidi Muehlebach of Vigilance Technologies, Warwick, Queensland, Australia, 6 February 2019.

Abstract for the machine vision report

The purpose of the project was to develop an intelligent deterrent system that detects, identifies and then deters wildlife using static or autonomous vehicles equipped with species-specific deterrents. The ability to detect and identify wildlife will enable deterrent strategies to be tailored to specific species and also allow the system to document its own performance by determining the type and number of wildlife species in the field-of-view.

The intelligent detection–deterrent system that has been developed in this project uses state-of-the-art machine vision algorithms combined with the latest security cameras. This opens a wide range of possibilities for the use of the system beyond the role of detecting and identifying birds. Machine vision, when trained correctly, has the ability to outperform humans in tasks that require observation of subtle differences between recognised images.

On-farm trials have demonstrated that the machine vision system developed in this project was able to be trained to identify several species of wild birds with a high degree of accuracy, record wild bird activity, and activate deterrents. Static deterrents were trialled, but found to be ineffective at deterring birds from large areas, including farm dams.

Further research is required to develop more effective deterrent techniques.

We recommend that autonomous, mobile deterrents be developed to improve deterrent effectiveness.

Appendix 2: Selected images

Wild birds

Apostlebird near range

Apostlebird on feedline

Apostlebirds near range

Australasian Pipit on fence

Australasian Pipit on temporary surface water

Australasian Pipit under silo

Australian Brush Turkeys at feed spill

Australian Magpie-Larks

Australian Magpie-Larks

Australian Magpie-Larks

Australian Magpies on range

Australian Pelican

Australian Raven

Australian White Ibis

Australian White Ibis

Australian Wood Duck

Black Kite in water

Black-fronted Dotterel (native Charadriidae)

Bush Stone-curlew

Cattle Egret

Chestnut Teal

Chestnut Teal, Eurasian Coot, Grey Teal

Chickens – escapees feeding at silo

Chickens drinking from water leak

Crested Pigeon

Double-barred Finches

Dusky Moorhen

Fairy Martin nests

Fairy Martin nests

Galah

Great Egret

Grey Teal (with Australian Pelican)

House Sparrow

Latham's Snipe

Latham's Snipe

Laughing Kookaburra

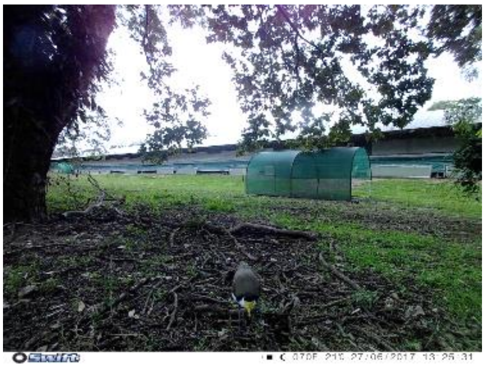
Laughing Kookaburra

Magpie

Masked Lapwing

Masked Lapwing

Masked Lapwing



Masked Lapwing

Pacific Black Duck

Peaceful Doves and Crested Pigeons

Pelicans

Pheasant Coucal

Pied Butcherbird

Plumed Whistling-Duck

Plum-headed Finch (male)

Plum-headed Finches

Purple Swamphen

Purple Swamphen

Australian Raven (deceased) on range

Straw-necked Ibis

Straw-necked Ibis

Straw-necked Ibis

Straw-necked Ibis with chickens

Striated Pardalote

Striated Pardalote (2)

Torresian Crow

White-Faced Heron

White-Necked (Pacific) Heron

Mammals and reptiles

Brush-Tailed Possum

Eastern Water Dragon

Fox

Goats

Red-necked Wallaby

Red-necked Wallaby

Red-necked Wallaby

Red-necked Wallaby

Red-necked Wallaby

Red-necked Wallaby

Sheep

Other relevant photos

Apostlebird drinking point next to range

Camera mounted on fence post

Cobwebs on surveillance camera

AgriFutures®
Chicken Meat

Detect-alert-deter system for enhanced
biosecurity and risk assessment

by Michael Atzeni, John Muehlebach, Darren Fielder and David Mayer
September 2020

Publication No. 20-089
Project No. PRJ-010264
ISBN: 978-1-76053-118-8

AgriFutures Australia

Building 007
Tooma Way
Charles Sturt University
Locked Bag 588
Wagga Wagga NSW 2650

02 6923 6900
info@agrifutures.com.au

@AgriFuturesAU
agrifutures.com.au