Supplementary Information

Potential for Artificial Intelligence (AI) and Machine Learning (ML) Applications in Biodiversity Conservation, Managing Forests, and Related Services in India

Kadukothanahally Nagaraju Shivaprakash [1,*], Niraj Swamy [2], Sagar Mysorekar [1], Roshni Arora [1], Aditya Gangadharan [1], Karishma Vohra [1], Madegowda Jadeyegowda [3] and Joseph M. Kiesecker [4]

[1] The Nature Conservancy Center, 37 Link Road, Lajpatnagar-3, New Delhi 110024, India

[2] The Nature Conservancy, Arington, VA 22201, USA

[3] College of Forestry, Keladi Shivappa Nayaka University of Agricultural and Horticultural Sciences, Ponnampet 571216, India

[4] Global Lands Program, The Nature Conservancy, Fort Collins, CO 80524, USA

* Corresponding author: shivaprakash.kn@tnc.org

Table S1. Summary of AI and machine learning application research in biodiversity conservation and forest sector.

Major Sector	Area of Application	Specific Application	Taxa or Ecosystem	Technology and Algorithm	Reference
Terrestrial biodiversity conservation	Wildlife inventory, protection, and management	Identification and taxonomy	Mammals	Computer vision (AI tools that can instantly classify species based on images and videos)	Trnovszky et al. 2019; Tabak et al. 2018; Chen et al. 2014; Van Horn et al. 2018; Falzon et al. 2020; Nguyen et al. 2017; Gomez et al. 2017; Yu et al. 2013; Willi et al. 2018; Wilber et al. (2013); Gomez et al. (2016); Weinstein et al. 2017; Van Horn et al. 2018; Joppa 2017; Shukla et al. 2019
			Mammals	Automated acoustic using neural networks and deep learning	Vaughan et al. 1997, Parsons and Jones 2000, Parsons 2001; Murray et al. 1998; Nuñez et al. 2018; Berno 2019; Wisler et al. 2016
			Birds	Image recognition technique using CNN	Van Horn et al. 2018; Chen et al. 2018; (Gavves et al., 2015; Berg et al., 2014; Berg and Belhumeur, 2013; Huang et al., 2013; Branson et al., 2014; Duan et al., 2012; Atanbori et al. 2018; Atanbori et al. 2016; Gavali et al 2019; Burghardt and Campbell 2007; Branson et al. 2014; Xu and Zhu 2016; Bowley et al. 2016; Van Horn et al. 2018;

					Sullivan et al. 2018
			Birds	Automated acoustic using neural networks and deep learning	Vaca-Castano and Rodriguez (2010); Huang et al. (2009); Acevedo et al. (2009); Brandes (2008); Mills 1995; McIlraith and Card 1995, Anderson et al. 1996; Terry and McGregor 2002; Kershenbaum et al. 2016; Mporas et al. 2012;
			Amphibians	Automated acoustic using neural networks and deep learning	Yuan and Ramli 2013; Noda et al. 2016; Tan et al. 2014; Xie et al. 2015a, b,c,d; Xie et al. (2016); Colonna et al. (2015); Bedoya et al. (2014); Tan et al. (2014); Huang et al. (2014); Jaafar and Ramli (2013); Jaafar et al. (2013a,b); Gingras and Fitch (2013); Camacho et al. (2011); Chen et al. (2012); Colonna et al. (2012); Croker and Kottege (2012); Han et al. (2011); Dayou et al. (2011); Vaca-Castano and Rodriguez (2010); Huang et al. (2009); Lee et al. (2006); Dang et al. (2008); Huang et al. (2008); Brandes et al. (2006); Grigg et al. (1996); Yen and Fu (2002); Xie et al. 2016; Chao et al. 2019; Colonna et al.

					2016; Taylor et al. 1996
			Insects	Image recognition technique using CNN	Hernandez-Serna et al (2014); Feng et al. (2016)
			Coral, benthic invertebrates and fish	Image recognition technique using CNN	Qin et al. (2016); Villon et al. (2016); Sun et al. (2016); Marburg & Bigham (2016); Beijbom et al. (2016); Hernandez-Serna et al (2014); Beijbom et al. 2015; Johnson-Roberson
			Insects	Automated acoustic using neural networks and deep learning	Brandes (2008); Lee et al. (2006); Brandes et al. (2006); Weeks et al. 1999; Campbell et al. 1996; Ohya and Chesmore 2003; Chesmore et al. 1997, Chesmore 2001, Chesmore and Nellenbach 2001, Schwenker et al. 2003; Chesmore 2004
		Wildlife census and monitoring	Mammals	Image recognition technique using neural network and deep learning	Sirmacek et al. 2012; Borowicz et al. 2019; Guirado et al. 2018; Norouzzadeh et al. 2018; Xue et al. 2017; Kellenberger et al. 2018; Corcoran et al. 2019; Gonzalez et al. 2016; Torney et al. 2019; Brust et al. 2017; K¨orschens et al. 2017; Norouzzadeh et al. 2019; Tabak et al. 2018; Chen et al. 2014; Villa et al. 2017;

					Nguyen et al. 2017; Reby et al. 1997; Clemins and Johnson 2002; Bjorck et al. 2019; Bergler et al. 2018; Garcia et al. 2020; Nuñez et al. 2018; Aodha et al. 2018
			Birds	Image processing and classification using neural network and deep learning	Abd-Elrahman et al. 2005; Desell et al. 2013; Dickinson et al. 2008; Groom et al. 2011; Liu et al. 2015; Qing et al. 2011; Weinstein 2014; Bajzak and Piatt 1990; Buckland et al. 2012; Descamps et al. 2011; Trathan 2004; Press and Laliberte 2003; Fretwell et al. 2012; Witharana and Lynch 2016; Lynch et al. 2012; Barber-Meyer 2007; Aide et al. 2013
		Diversity estimation	Birds	AI and ML based statistical algorithms	Brandes 2008; Burivalova et al. 2019; Wood et al. 2019; González-Rivero et al. 2020; Aide et al. 2013; Villon et al. 2018
			Amphibians	AI and ML based statistical algorithms	Taylor et al. 1996
	Animal behaviour and welfare		Birds, mammals, frogs, fish	Pattern recognition, image recognition and automated bioacoustics	Kembhavi 2008; Mcdowall and Lynch 2017; Luque et al. 2017; Rew et al. 2019; Yamazaki et al. 2019; Graving et al. 2019; Han et al. 2019; Hirakawa et al. 2018;

					Oliver et al. 2018; Ehsani et al. 2018; Mearns et al. 2020; Browning et al. 2017; Brewster et al. 2018; Kabra et al. 2013; Dell et al. 2014; Valletta et al. 2017; Weinstein et al. 2016; Goehner et al. 2015; Burivalova et al. 2019; Metcalf et al. 2018; Azzellino et al. 2011; Andre´2018; Senzaki et al. 2016; Dunlop et al. 2017; Mcloughlin et al. 2019; Turesson et al. 2016; Pereira et al. 2019; Metcalf et al. 2019
	Detecting and predicting threat to wildlife	Illegal wildlife trade		Image recognition	Minin et al. 2018; Minin et al. 2019; Hernandez-Castro et al. 2015; Hernandez-Castro et al. 2016
		Detecting and predicting poaching		Image and pattern recognition	Chalmers et al.2019; Bondi et al. 2018a,b; Xu et al. 2019; Banzi 2014; Mishra et al. 2010; Park et al. 2015; Kar et al. 2017; Grange 2019; Fang et al. 2015
Forest and terrestrial biodiversity	Monitoring ecosystem health			Automated bioacoustics using deep learning	Aide et al. 2013; Burivalova1 et al. 2019; González-Rivero et al. 2020; Kroodsma et al. 2018; Nay et al. 2016
	Predicting diversity processes	Species diversity estimation	Birds	AI and ML based statistical algorithms	Brandes 2008; Burivalova et al. 2019; Wood et al. 2019; González-Rivero et al. 2020;

					Aide et al. 2013; Villon et al. 2018; Park et al. 2003; Salamon et al. 2017; Gil-Tena et al. (2010)
			Amphibians, Fishes, Insects	AI and ML based statistical algorithms	Lek-Aug et al. 1999; Lek et al., 1996; Guegan et al. 1998; Taylor et al. 1996; Chon et al. 1996; Park et al. 2003; Villon et al. 2018
		Predicting species extinction status		AI and ML based statistical algorithms	Pelletier et al. 2018; Darrah et al. 2017; Brilliantova et al. 2018; Bland et al. 2015
Aquatic biodiversity	Monitoring	Monitor and map ecosystems and their condition	Freshwater and Marine	Pattern recognition, image recognition using deep learning	Nunes et al., 2020; Watts et al., 2011; Manté et al., 2014; Palaniswami et a., 2017; Berberoglu et al., 2004; Mohiuddin, 2014; Pereira et al., 2011;
		Monitor commercial fishing; fishing intensity	Freshwater and Marine	AI and ML based statistical algorithms	Kroodsma et al., 2018; Benzer et al.,2015; Álvarez-Ellacuría et al 2020; Russo et al., 2019;
		Monitor endangered/threatened species	Marine	Pattern recognition, image recognition and automated bioacoustics	Gray et al., 2019; Hodgson et al., 2013; Bevan et al., 2015;
		Monitor marine mammals, whales in particular	Marine	Pattern recognition, image recognition and automated bioacoustics	https://www.blog.google/technology/ai/protecting-orcas/
		Water quantity and quality		AI and ML based statistical algorithms	Fijani et al., 2019; Gunda et al., 2019; Hatzikos et al., 2007; Sharaf et al., 2017; Strobl & Robillard, 2006; Ceccaroni et al., 2018; Zhu et

					al., 2010; Sengorur et al., 2015; Khaki et al., 2015; Gharibi et al., 2012; Li et al., 2016; Hatzikos et al., 2008;
	Forecasting/Predictions	Water quality and quantity	Freshwater	AI and ML based statistical algorithms	Hameed et al., 2017; Chang et al., 2015; Najah et al., 2011; Rajaee et al 2020; Tung et al., 2020; Fathian et al., 2019; Toro et al., 2013; Chau, 2006; Ceccaroni et al., 2018; Wang et al., 2019; Yaseen et al., 2016; Coad et al., 2014; Elkiran et al., 2019; Najah et al., 2009; Barzegar et al., 2016; Sakizadeh, 2016;
		Biodiversity	Tidal	AI and ML based statistical algorithms	Yoo et al., 2013
		Extinction probabilities		AI and ML based statistical algorithms	Cheung et al., 2005;
		Toxicity in organisms		AI and ML based statistical algorithms	Singh et al., 2013; Sengar et ak., 2017
		Organism dispersal	Marine	AI and ML based statistical algorithms	Pontin et al., 2011
		Species/habitat distributions	Freshwater and Marine	AI and ML based statistical algorithms	Zarkami et al., 2012; Olaya-Marín et al., 2013; Mastrorillo et al., 1997; Muñoz-Mas et al., 2015; Palialexis et al., 2011; Pittman & Brown, 2011; Volf et al 2011; Gillard et al., 2017; Flombaum et al., 2013; Park et al., 2006; Guénard et al., 2020

	Species detection/identification/classification/behaviour		Marine	Pattern recognition, image recognition and automated bioacoustics	Siddiqui et al., 2018; Villon et al., 2018; Allken et al 2019; dos Santos et al., 2019; Labao et al., 2019; Salman et al., 2020; Xu et al., 2019; Bedoya et al., 2014; Liu et al., 2011; Mosleh et al., 2012; Song et al., 2015; Xia et al., 2018;
	Assessments	To estimate abundance/richness	Freshwater	AI and ML based statistical algorithms	Marini et al., 2018; Recknagel, 1997; Park et al., 2003; Mandal et al., 2018; Tang et al., 2014;
		Abiotic-biotic relationships	Freshwater	AI and ML based statistical algorithms	Hu et al., 2020; Tsai et al., 2017; Olden et al., 2001; Knudby et al., 2010; Kocev et al., 2010; Schletterer et al., 2010; Feio et L., 2011; Tsai et al., 2017;
		Community ecology/diversity/structure/function	Freshwater	AI and ML based statistical algorithms	Brosse et al., 2001; Moitinho-Silva et al., 2017; Brey, 2012; Gutie´rrez-Estrada et al 2006; Awad 2014; Franceschini et al 2019; Goethals et al., 2007; Quetglas et al., 2011; Lachkar et al., 2012; Penczak et al., 2012; Cheng et al., 2012;
	Aquaculture	Fish feeding intensity	Freshwater	AI and ML based statistical algorithms	Zhou et al., 2019;
Forest	Plant inventory and identification			Image recognition technique using neural network and deep learning	Sun et al. 2017; WaÈldchen et al. 2018; Aziah et al. 2019
	Predicting diversity	Predicting species		AI and ML based	Bland et al. 2015; Pelletier et

	processes	extinction status		statistical algorithms	al. 2018; Darrah et al. 2017;
	Forest health and phenology monitoring			Image recognition technique using neural network and deep learning	Nay et al. 2018; Burivalova et al. 2019; Xulu et al. 2019; Park et al. 2019; Correia et al. 2020
	Forest classification and mapping			Image recognition technique using neural network and deep learning	Carreiras et al. 2006; Lin et al. 2019; Brodrik et al. 2019; Watanabe et al. 2018
	Forest resource quantification and mapping	Quantifying and mapping biomass and carbon stock		ANNs combined with traditional models	Were et al. 2015; Dao et al. 2019; Montaño et al. 2017; Deb et al. 2017
		Quantifying and mapping ecosystem services		AI and ML based statistical algorithms to quantify ecosystem services	Chen et al. 2014; Villa et al. 2009; Lee et al. 2019; Willcock et al. 2018
	Forest restoration and conservation			Automated seed planting and AI algorithm to identify suitable habitat for restoration	Fromm et al. 2019; Khan and Gupta 2018
	Detecting and predicting anthropogenic threat to forest	Mapping deforestation		Pattern recognition, and image recognition using deep learning	Ahmadi 2018; Duo et al. 2019; Hufkens et al. 2020
	Hazard assessment and prediction	Predicting and detecting forest fire		Pattern recognition, and image recognition using deep learning	Sakr et al. (2010); Satir et al. 2016; Zhang et al. 2019; Bui et al. 2017
		Predicting and detecting pest and diseases outbreak		AI and ML based statistical algorithms to recognize the pattern	Bilski et al. 2017; Golhani et al. 2018; Rammer and Seidl (2018); Wiesner-Hanks et al. 2019
		Predicting alien species invasion		Image recognition technique using neural network and deep learning	Pu et al. 2008; Ismail et al. 2016; Martinez et al. 2019; Dash et al. 2019

	Illegal felling and wood trafficking	Detecting illegal felling		Pattern recognition, image recognition and automated bioacoustics	Chen and Liaw 2017; Kalhara et al. 2017; Ahmad and Singh 2019; Prasetyo et al. 2018
		Tracking illegal timber trafficking		Pattern recognition, image recognition and automated bioacoustics	Tang et al. 2017
	Predicting vegetation and species response to climate change			AI and ML based statistical algorithms to recognize the pattern	Ostendorf et al. 2001; Rammer and Seidl 2019; Evans et al.2011; Périé and de Blois (2016)
	Timber harvesting			AI and ML based statistical algorithms to recognize the pattern	Hokans 1984; Çalişkan 2019; John et al. 2016; Lindroos et al. 2017; Proto et al. 2020
	Predicting supply and demand of forest resource			AI and ML based statistical algorithms to recognize the pattern	Milovanović et al. 2017; Anandhi et al. 2012.; Zhao and Yuhe (2020)
	Forest hydrology	Modeling precipitation interception by forest canopies and water content in forest canopies Terrestrial vegetation and ground water storage		AI and ML based statistical algorithms to recognize the pattern	Stravs et al., 2008; Dube et al., 2017; Trombetti et al., 2008 Luo et al., 2020; Irrgang et al., 2020; Bhanja et al., 2019; Kamarudin et al., 2021
		Spatiotemporal behaviour of soil moisture in vegetated areas		AI and ML based statistical algorithms to recognize the pattern	Lee et al., 2018; Zhang et al., 2021; de Oliveira et al., 2021
		Vegetation evapotranspiration, and water-use efficiency in terrestrial ecosystems		AI and ML based statistical algorithms to recognize the pattern	Lu and Zhuang, 2010; Panda et al., 2018; Pan et al., 2020

Table S2. AI start-up companies and non-profits in biodiversity conservation and forest sector.

Sector	Start-Up Name	Location	Application	Approach
Forest	20trees.AI (https://solarimpulse.com/companies/20tree-ai) (accessed on 15 June 2021)	Portugal	Real-time forest inventory & sustainable forest management (forest inventory, tree growth and productivity, biomass harvesting, monitoring threat to forest and forest health	Use remote sensing, big data, cloud computing and artificial intelligence for real-time forest inventory and monitoring.
Forest	aiTree (http://aitree.ltd/) (accessed on 15 June 2021)	Canada	Solving demand and supply problem in forestry sector (wildlife habitat, biodiversity, water quality, visual quality, carbon storage, improving decisions on timber allocations and conserving natural areas for ecosystem services.).	Use Artificial Intelligence, Big Data and Cloud computing technologies to solve the complicated Demand & Supply problems in Canadian forests.
Forest	ByteLAKE (https://www.bytelake.com/en/case-studies/case-study-counting-trees-with-drones/) (accessed on 15 June 2021)	USA	Restoration and forest monitoring	Company AI platform software dubbed as Ewa Guard uses images captured by drones to count planted seedlings and trees in forest.

Forest	CollectiveCrunch (https://www.collectivecrunch.com/) (accessed on 15 June 2021)	Germany, Finland	Mapping and predicting wood mass, wood species and wood quality of target areas.	The start-up developed an innovative AI platform dubbed as Linda Forest, which is a turn-key SaaS solution that predicts wood mass, wood species and wood quality of target areas far more accurate than any existing conventional methods. The company utilizes climate, geo, and customer process data to make better predictions of forest inventory. Then based on this prediction advise forestry firms about what quality and quantity of wood they are buying.
Forest	Dendra (https://dendra.io/) (accessed on 15 June 2021)	UK	Automated and cost-effective reforestation	Use artificial intelligence-based automation and digital intelligence to identify suitable planting area and disperse seedpods filled with seeds of desired species and nutrients for germination in identified plant location. With Dendra's technology, 10

				billion trees can be planted each year and in often hard accessible places
Forest	Droneseed (https://droneseed.com/) (accessed on 26 June 2021)	USA	Automated and cost-effective reforestation	Use artificial intelligence-based automation and digital intelligence to identify suitable planting area and disperse seeds of desired species along with nutrients from innovative product called seed vessels. Land Life is on a mission to reforest the world's 2 billion hectares of degraded land.
Forest	Erol Foundation, the Center for Global Discovery, and Conservation Science (GDCS) at ASU and Planet.Inc (https://csteps.asu.edu/new-satellite-system-can-map-tropical-forest-carbon-emissions) (accessed on 15 June 2021)	Peru	Automatic and cost-effective direct measurement and mapping of carbon stock and emission at high resolution.	Use computer vision models, LiDAR, and satellite imagery at 3-5m resolution for automatic and cost-effective direct measurement and mapping of carbon stock and emission at high resolution and high frequency in Peruvian forest.
Forest	Finnish Forest Centre (https://www.metsakeskus.fi/en) (https://www.esri.com/about/newsroom/blog/finland-enhances-forest-data-accuracy-for-automation/) (accessed on 15 June	Finland	Forest inventory and accurate measurement of	Use GIS data, imagery sources, climate and weather data and artificial

	2021)		forest stand.	intelligence for accurate measurements of forest stands and to better predict forest inventory.
Forest	Future Forest Map Project (https://www.futureforestmap.ethz.ch/) (accessed on 26 June 2021)	Borneo	High resolution past and future forest changes in Borneo (Indonesia) to support actors in forest conservation	Use artificial intelligence to harvest the information from the vast amount of satellite imagery and also to learn to see where and when deforestation will occur by modelling the direct drivers from satellite images.
Forest	GainForest (https://www.gainforest.app/) (accessed on 26 June 2021)	USA, Switzerland, and Spain	To monitor and forecast forest change at high resolution and design carbon payment scheme.	Use large amounts of unlabelled satellite imagery, video prediction model, game theory and machine learning based Measurement, Reporting and Verification (MRV) processes to monitor and forecast deforestation and design carbon payment scheme.
Forest	Global Forest Watch (https://www.globalforestwatch.org/) (accessed on 27 June 2021)	USA	Global monitoring of deforestation rate in real time	Use satellite imagery and artificial intelligence to monitor the global forest for deforestation in real

				time.
Forest	Land Life (https://landlifecompany.com/) (accessed on 27 June 2021)	Amsterdam	Low-cost, sustainable, and scalable solution to reforestation	The Dutch start-up uses GPS, satellite imagery, Cocoon (a seedling support technology), automated planting technique and AI technology for mass scale reforestation and also for monitoring reforestation successes.
Forest	MAPIZY (https://www.mapizy.com/usecase.html) (accessed on 15 June 2021)	Australia	Forest inventory and biodiversity monitoring	Use combination of high-resolution satellite images, crowd sourced images, deep learning and other AI technology for forest inventory and biodiversity monitoring.
Forest	Outland Analytics (https://blog.particle.io/cellular-iot-forest-protection/) (accessed on 15 June 2021)	USA	Real time monitoring of illegal logging and timber theft, protection of natural areas	Uses audio recognition artificial intelligence algorithms to detect chainsaw sound or unauthorized vehicle and send real time alert via email to official to efficiently manage environmental crime.

Forest	Pachama (https://pachama.com/) (accessed on 15 June 2021)	USA	Carbon offsetting to preserve forest and encourage reforestation	Uses machine learning on a combination of satellite, drone, and lidar images to precisely estimate individual tree size, volume, and carbon density.
Forest	PlantSnap (https://www.plantsnap.com/), Pl@ntNet (https://identify.plantnet.org/), Flora Incognita (https://floraincognita.com/), PictureThis (https://www.picturethisai.com/), PlantSpot (https://plantspot.app/) (accessed on 2 August 2021)		Plant species identification	Identify plant species using database of images
Forest	Satelligence (https://satelligence.com/) (accessed on 26 June 2021)	Netherlands	Leverages satellite data to fight deforestation and protecting natural resources	By combining satellite images and Artificial Intelligence (AI), the start-up provides up-to-date information on worldwide deforestation, causes and trends.
Forest	SILVIATERRA (https://ncx.com/) (accessed on 26 June 2021)	USA	Forest inventory, quantifying biomass, carbon sequestration and ecosystem services at individual tree level.	Use remote sensing, big data, cloud computing and artificial intelligence to accurately assess forest for biodiversity, biomass, and ecosystem services.
Forest	Terrafuse (https://www.terrafuse-ai.com/) (accessed on 26 June 2021)	Canada	Predicting and mapping wildfire in forest	Use physics-enabled AI models to understand

				climate-related risk at the hyperlocal level. Terrafuse leverages historical wildfire data, numerical simulations, and satellite imagery on Microsoft Azure to model wildfire risk for any location. It also estimates temporal change in carbon density as a result of fire, deforestation and other calamities.
Forest	TerraMonitor (https://www.terramonitor.com/labs) (accessed on 26 June 2021)	Finland	Monitoring deforestation and forest health in real time.	Uses database of satellite images collected everyday by multiple satellites and artificial intelligence to create low cost satellite data for natural area management and also monitor deforestation and forest health in real time. Besides an accurate report of logging, the startup promises to improve the way forests are managed and grown, by detecting changes in biodiversity, determining biomass and

				finding out the ratio of various tree types.
Forest	Tesselo (https://tesselo.com/solutions-for-sustainability) (accessed on 26 June 2021)	Portugal	Tackling natural disasters such as forest fires.	Use satellite images and AI to tackles natural disasters, such as forest fires. Using its technology, besides estimating risk or impact of forest fires, start-up also predict the growth of the forest, monitor crops, and even detect pests.
Forest	Timbeter (https://timbeter.com/) (accessed on 26 June 2021)	Estonia	Precision forestry for optimising forestry, securing legal trade, and fighting illegal logging.	Uses world's largest database of photometric measurements of roundwood and artificial intelligence for online tracking of roundwood to individual shipments and piles to fight illegal logging.
Forest	Xylene (https://galileo-masters.eu/winner/xylene-boosting-trust-in-timber/) (accessed on 26 June 2021)	Germany	Real time tracking of wood supply chain to combat illegal wood supply and to achieve sustainable forestry.	Uses combines of space technology, blockchain and supply chain mapping, automatic data gathered by IoT devices and Earth Observation and AI technology to track wood

				supply chain.
Forest	INTEGRAL (https://plus.maths.org/content/understanding-biodiversity-forests-using-ai) (accessed on 27 February 2022)	India, UK	A project which aims to understand the diversity of forests in India	Use semi-supervised learning technique to identify tree species from aerial images.
Forest and wildlife	Conservation X Labs (https://conservationxlabs.com/) (accessed on 5 July 2021)	USA	Identifying solutions to the underlying drivers of human-induced extinction of wildlife.	Use social media, crowd sourced image data, DNA technology and artificial intelligent to detect illegal wildlife and timber trade both in field and online.
Forest and wildlife	Gramener (https://gramener.com/aiforgood/) (accessed on 5 July 2021)	Australia	Identification and population census of endangered species. Land mapping.	Use artificial intelligence and remote sensing to identify and count endangered species to aid in their conservation. Also use artificial intelligence and high-resolution satellite data map land use pattern to plan conservation.
Forest and wildlife	iNaturalist (https://www.inaturalist.org/) (accessed on 5 July 2021)	USA	Flora and fauna identification	Use artificial intelligence and crowd sourced images data to identify flora and fauna.
Forest and	Naturalis Biodiversity Center, Observation.org, and COSMONiO (https://www.linkedin.com/pulse/collaboration-	Netherland	Collaboration to support and improve biodiversity	The collaboration will focus on using modern

wildlife	started-support-biodiversity-research-katramados) (accessed on 5 July 2021)		research through artificial intelligence	machine learning techniques, such as deep learning, to provide easy tools to identify and search through digitized biodiversity data.
Forest and wildlife	Rainforest Connection (RFCx) (https://rfcx.org/) (accessed on 26 June 2021)	USA	Prevent deforestation, halt animal poaching, and monitor forest ecosystem through bioacoustics monitoring.	Uses recycled android phoned powered by portable solar panels, bioacoustics, and machine learning to identify illegal logging and animal poaching in the forest.
Wildlife	Chirpomatic (http://www.chirpomatic.com/), Warblr (https://www.warblr.co.uk/), Merlin (https://merlin.allaboutbirds.org/) (accessed on 5 July 2021)	USA, UK	Birds' species identification apps	Identify bird species using database of bird songs and images
Wildlife	Connected Conversation (https://www.cisco.com/c/en/us/about/csr/impact/environmental-sustainability/connected-conservation.html) (accessed on 5 July 2021)	Collaboration between Dimension Data and Cisco Systems, South Africa	Protect global wildlife through the use of modern technology	Uses thermal imaging, IoT and artificial intelligence face recognition technology to send real time alerts to rangers about poachers inside park.
Wildlife	Conservation Metrics (https://conservationmetrics.com/) (accessed on 5 July 2021)	USA	Wildlife monitoring and diversity estimation	Uses cutting-edge remote sensing technology, artificial intelligence, statistical rigor, and extensive scientific

				expertise to drive down costs and increase the scale and effectiveness of wildlife monitoring and assessing diversity.
Wildlife	DeepMind (https://www.deepmind.com/blog/using-machine-learning-to-accelerate-ecological-research) (accessed on 5 July 2021)	UK	Wildlife census and management	Uses machine learning to detect and count animals, using millions of pictures taken in the Serengeti National Park in Tanzania.
Wildlife	EarthRanger (Vulcn.inc) (https://www.earthranger.com/) (accessed on 5 July 2021)	USA (online flatform)	Wildlife management in parks and halt poaching to aid endangered species conservation.	Uses artificial intelligence, predictive analytics, and radio collared animal and patrol data for real time monitoring and management of wildlife in parks.
Wildlife	eBird (https://ebird.org/home) (accessed on 5 July 2021)	USA	Identifying bird species, monitoring paths of migratory birds in real time, predicting suitable habitats for birds	Uses crowd sourced bird data and artificial intelligence to identify bird species in real time (Merlin app), to predict where there will be changes in habitat for certain species, and the paths along which birds will move during

				migration.
Wildlife	Global Fishing watch (https://globalfishingwatch.org/) (accessed on 5 July 2021)	International non-profit	Promote ocean fish and seafood sustainability and conservation of ocean biodiversity.	Use advanced remote sensing technology, satellite imagery and artificial intelligence to share data about global fishing activity in real time.
Wildlife	Goddard Space Flight Center (NASA) (https://www.nasa.gov/goddard) (accessed on 5 July 2021)	USA	Identifying and monitoring population of different species of phytoplankton in ocean to mitigate climate change	Researchers planning to use satellite imagery from PACE (for "Pre-Aerosol Clouds and ocean Ecosystem") and artificial intelligence to identify, monitor and predict individual species population of phytoplankton across globe to mitigate climate change.
Wildlife	OceanMind (https://www.oceanmind.global/) (accessed on 5 July 2021)	England	Preventing illegal, unreported, and unregulated fishing by analysing vessel movements in real time. AI algorithms identify suspicious behaviour, which OceanMind shares with agencies to direct patrol	Use satellites and AI to preserve biodiversity, protect livelihoods, and prevent slavery in the seafood industry

			boats more effectively.	
Wildlife	Penguin Watch (https://www.zooniverse.org/projects/penguintom79/penguin-watch) (accessed on 5 July 2021)	UK	Penguin population count and identification	Use crowd-sourced annotated images and density-based deep learning algorithms for accurate identification and population count of Individual Penguin species.
Wildlife	Project Zamba (https://zamba.drivendata.org/) (accessed on 5 July 2021)	Open global platform	Wildlife identification and conservation	Uses artificial intelligence and computer vision to evaluate the thousands of video material captured in camera trap to automatically recognise irrelevant information and retain only animal recordings.
Wildlife	Protection Assistant for Wildlife Security (PAWS) (https://sc.cs.cmu.edu/research-detail/102-protection-assistant-for-wildlife-security) (accessed on 5 July 2021)	USA	To aid conservation in the fight against animal poaching	PAWS collect information from previous poaching activities, then uses machine learning and behavioral modeling to generate predictions about poaching locations and optimal patrol routes. Therefore, outcome is more effective patrols and

				better use of resources in the fight against poaching vulnerable species.
Wildlife	Reefscape project (https://www.oneearth.org/reefscape-a-global-reef-survey-to-build-better-satellites-for-coral-conservation/) (accessed on 5 July 2021)	Australia	Global coral reef monitoring for conservation	Use artificial intelligence and drone mounted camera images to accurately survey reefs and assess the composition and health of coral reefs under the water over time.
Wildlife	RESLOVE (https://www.resolve.ngo/trailguard.htm) (accessed on 5 July 2021)	Collaboration between non-profit RESLOVE and Intel, USA	Protect global wildlife through the use of modern technology	Uses technology called TrailGuard AI, which detects humans among motion activated camera traps using image processing, deep neural network algorithms for object detection and image classification. Then triggers electronic alerts to park personnel to stop poaching.
Wildlife	WhaleShark.org, sharkbook.ai (https://www.sharkbook.ai/) (accessed on 5 July 2021)		Whales and shark's species identification	Cutting-edge AI software supports rapid identification using pattern recognition and photo management tools

Wildlife	Wild Me (https://www.wildme.org/#/) (accessed on 5 July 2021)	USA	Identifying and Conserving species that are on the verge of extinction	Use citizen science data, artificial intelligence, and cloud computing to power Wildbook, a platform that utilizes technology to scan and identify individual animals and species
Wildlife	Wildbook (https://lynx.wildbook.org/) (accessed on 5 July 2021)	USA	Population census and analysis and species conservation	Wildbook blends structured wildlife research with artificial intelligence, citizen science, and computer vision to speed population analysis and develop new insights to help fight extinction.
Wildlife	WildTrack (https://wildtrack.org/) (accessed on 5 July 2021)	USA	Non-invasive wildlife monitoring and identification	Uses database of footprint images and artificial intelligence to monitor and identify animals in the wild.
Aquatic and marine biodiversity	The AIME project (Artificial Intelligence for Marine Ecosystems) (https://www.afd.fr/en/presse-release/artificial-intelligence-in-support-of-marine-biodiversity) (accessed on 1 June 2022)	Franco-African consortium: Université Cadi Ayyad (Morocco), Université de Yaoundé (Cameroon), the Medical Imaging and Bioinformatics	The AIME project will provide valuable tools to support decision-making for coastal marine ecosystem management strategies	This project targets three scientific challenges: (1) the combination or hybridization of AI techniques aimed at improving the accuracy and precision of biodiversity indicators; (2)

		Laboratory at Université Gaston Berger de Saint-Louis (Senegal), ENTROPIE, a Mixed Research Unit working on the tropical marine ecology of the Pacific and Indian Oceans (New Caledonia, France), and the Research Institute for Development and Marine biodiversity, exploitation and conservation (France).		the development of multi-scale indicators reflecting the various health aspects and pressures facing marine ecosystems; and (3) their integration in an AI model capable of explaining and predicting the spatial and temporal dynamics of marine biodiversity in case studies.
Aquatic and marine biodiversity	The SMART-BIODIV project (Artificial Intelligence Technologies for Biodiversity Research) (https://www.afd.fr/en/presse-release/artificial-intelligence-in-support-of-marine-biodiversity) (accessed on 1 June 2022)	Franco-American consortium: Georgia-Tech (USA), Central Supelec Loria (France), the Interdisciplinary Laboratory for Continental Environments and the Laboratory of Oceanography of Villefranche (France)		It will develop new methods for managing and integrating biodiversity data from coastal marine environments using automatic learning algorithms to fill in missing data and develop suitable indicators for assessing the biodiversity of the areas observed. This project also proposes to make large data sets

				containing millions of images of planktonic organisms available to the scientific community.
	The FISH-PREDICT project (Predict Reef-Fish Biodiversity) (https://www.afd.fr/en/presse-release/artificial-intelligence-in-support-of-marine-biodiversity) (accessed on 1 June 2022)	The Marine biodiversity exploitation and conservation research unit, the Montpellier Laboratory of Informatics, Robotics and Microelectronics, the Center for Functional and Evolutionary Ecology (CEFE), Lab-STICC (a research laboratory in Information and Communication Science and Technology), and the Alpine Ecology Laboratory (LECA).	It aims to discover intelligent solutions for nature in order to strengthen the sustainability of coastal soo-ecological systems.	This project seeks to create ecological indicators and predictive models for the biodiversity of disturbed ecosystems by combining artificial intelligence methods with well-known assessment approaches. It will also result in the creation of the first knowledge base on marine biodiversity and, thereafter, the development of predictive and interpretative models.

References

Allken, V.; Handegard, N.O.; Rosen, S.; Schreyeck, T.; Mahiout, T.; Malde, K. Fish species identification using a convolutional neural network trained on synthetic data. *ICES J. Mar. Sci.* **2019**, *76*, 342–349.

Álvarez-Ellacuría, A.; Palmer, M.; Catalán, I.A.; Lisani, J.L. Image-based, unsupervised estimation of fish size from commercial landings using deep learning. *ICES J. Mar. Sci.* **2020**, *77*, 1330–1339.

Awad, M. Sea water chlorophyll-a estimation using hyperspectral images and supervised artificial neural network. *Ecol. Inform.* **2014**, *24*, 60–68.

Barzegar, R.; Adamowski, J.; Moghaddam, A.A. Application of wavelet-artificial intelligence hybrid models for water quality prediction: a case study in Aji-Chay River, Iran. *Stoch. Env. Res. Risk A* **2016**, *30*, 1797–1819.

Bedoya, C.; Isaza, C.; Daza, J.M.; López, J.D. Automatic recognition of anuran species based on syllable identification. *Ecol. Inform.* **2014**, *24*, 200–209.

Berberoglu, S.; Yilmaz, K.T.; Özkan, C. Mapping and monitoring of coastal wetlands of Cukurova Delta in the Eastern Mediterranean region. *Biodivers. Conserv.* **2004**, *13*, 615–633.

Bevan, E.; Wibbels, T.; Najera, B.M.; Martinez, M.A.; Martinez, L.A.; Martinez, F.I.; Cuevas, J.M.; Anderson, T.; Bonka, A.; Hernandez, M.H.; et al. Unmanned aerial vehicles (UAVs) for monitoring sea turtles in near-shore waters. *Mar. Turt. Newsl.* **2015**, *145*, 19–22.

Brey, T. A multi-parameter artificial neural network model to estimate macrobenthic invertebrate productivity and production. *Limnol. Oceanogr.-Methods* **2012**, *10*, 581–589.

Brosse, S.; Lek, S.; Townsend, C.R. Abundance, diversity, and structure of freshwater invertebrates and fish communities: An artificial neural network approach. *N. Zeal. J. Mar. Freshw.* **2001**, *35,* 135–145.

Ceccaroni, L.; Velickovski, F.; Blaas, M.; Wernand, M.R.; Blauw, A.; Subirats, L. Artificial intelligence and earth observation to explore water quality in the Wadden Sea. *Earth Obs. Open Sci. Innov.* **2018**, *15*, 311–320.

Chang, N.B.; Mohiuddin, G.; Crawford, A.J.; Bai, K.; Jin, K.R. Diagnosis of the artificial intelligence-based predictions of flow regime in a constructed wetland for stormwater pollution control. *Ecol. Inform*. **2018**, *28*, 42–60.

Chau, K.W. A review on integration of artificial intelligence into water quality modelling. *Mar. Pollut. Bull.* **2006**, *52,* 726–733.

Cheng, L.; Lek, S.; Lek-Ang, S.; Li, Z. Predicting fish assemblages and diversity in shallow lakes in the Yangtze River basin. *Limnologica* **2012**, *42*, 127–136.

Cheung, W.W.; Pitcher, T.J.; Pauly, D. A fuzzy logic expert system to estimate intrinsic extinction vulnerabilities of marine fishes to fishing. *Biol. Conserv.* **2005**, *124*, 97–111.

Coad, P.; Cathers, B.; Ball, J.E.; Kadluczka, R. Proactive management of estuarine algal blooms using an automated monitoring buoy coupled with an artificial neural network. *Environ. Model. Softw.* **2014**, *61*, 393–409.

dos Santos, A.A.; Gonçalves, W.N.; 2019. Improving Pantanal fish species recognition through taxonomic ranks in convolutional neural networks. *Ecol. Inform.* **2019**, 53, 100977.

Elkiran, G.; Nourani, V.; Abba, S.I. Multi-step ahead modelling of river water quality parameters using ensemble artificial intelligence-based approach. *J. Hydrol.* **2019**, *577*, 123962.

Fathian, F.; Mehdizadeh, S.; Sales, A.K.; Safari, M.J.S. Hybrid models to improve the monthly river flow prediction. Integrating artificial intelligence and non-linear time series models. *J. Hydrol.* **2019**, *575*, 1200–1213.

Feio, M.J.; Poquet, J.M. Predictive models for freshwater biological assessment: statistical approaches, biological elements and the Iberian Peninsula experience: a review. *Int. Rev. Hydrobiol.* **2011**, *96*, 321–346.

Fijani, E.; Barzegar, R.; Deo, R.; Tziritis, E.; Skordas, K. Design and implementation of a hybrid model based on two-layer decomposition method coupled with extreme learning machines to support real-time environmental monitoring of water quality parameters. *Sci. Total Environ.* **2019**, *648*, 839–853.

Flombaum, P.; Gallegos, J.L.; Gordillo, R.A.; Rincón, J.; Zabala, L.L.; Jiao, N.; Karl, D.M.; Li, W.K.; Lomas, M.W.; Veneziano, D.; et al. Present and future global distributions of the marine Cyanobacteria Prochlorococcus and Synechococcus. *Proc. Natl. Acad. Sci. USA* **2013**, *110*, 9824–9829.

Franceschini, S.; Mattei, F.; D'Andrea, L.; Di Nardi, A.; Fiorentino, F.; Garofalo, G.; Scardi, M.; Cataudella, S.; Russo, T. Rummaging through the bin: Modelling marine litter distribution using Artificial Neural Networks. *Mar. Pollut. Bull.* **2019**, *149*, 110580.

Gan, J.; Cerutti, P.O.; Masiero, M.; Pettenella, D.; Andrighetto, N.; Dawson, T. Quantifying illegal logging and related timber trade. *IUFRO World Ser.* **2016**, *35*, 37–59.

Gharibi, H.; Mahvi, A.H.; Nabizadeh, R.; Arabalibeik, H.; Yunesian, M.; Sowlat, M.H. A novel approach in water quality assessment based on fuzzy logic. *J. Environ. Manag.* **2012**, *112*, 87–95.

Gillard, M.; Thiébaut, G.; Deleu, C.; Leroy, B. Present and future distribution of three aquatic plants taxa across the world: Decrease in native and increase in invasive ranges. *Biol. Invasions* **2017**, *19*, 2159–2170.

Goethals, P.L.; Dedecker, A.P.; Gabriels, W.; Lek, S.; De Pauw, N. Applications of artificial neural networks predicting macroinvertebrates in freshwaters. *Aquat. Ecol.* **2007**, *41*, 491–508.

Gray, P.C.; Fleishman, A.B.; Klein, D.J.; McKown, M.W.; Bézy, V.S.; Lohmann, K.J.; Johnston, D.W. A convolutional neural network for detecting sea turtles in drone imagery. *Methods Ecol. Evol.* **2019**, *10*, 345–355.

Guénard, G.; Morin, J.; Matte, P.; Secretan, Y.; Valiquette, E.; Mingelbier, M. Deep learning habitat modeling for moving organisms in rapidly changing estuarine environments: A case of two fishes. *Estuar. Coast. Shelf Sci.* **2020**, *238*, 106713.

Gunda, N.S.K.; Gautam, S.H.; Mitra, S.K. Artificial intelligence based mobile application for water quality monitoring. *J Electrochem. Soc.* **2019**, *166*, B3031.

Hameed, M.; Sharqi, S.S.; Yaseen, Z.M.; Afan, H.A.; Hussain, A.; Elshafie, A. Application of artificial intelligence (AI) techniques in water quality index prediction: a case study in tropical region, Malaysia. *Neural Comput. Appl.* **2017**, *28*, 893–905.

Hatzikos, E.V.; Bassiliades, N.; Asmanis, L.; Vlahavas, I. Monitoring water quality through a telematic sensor network and a fuzzy expert system. *Expert Syst.* **2007**, *24*, 143–161.

Hatzikos, E.V.; Tsoumakas, G.; Tzanis, G.; Bassiliades, N.; Vlahavas, I. An empirical study on sea water quality prediction. *Knowl.-Based Syst.* **2008**, *21*, 471–478.

Hodgson, A.; Kelly, N.; Peel, D. Unmanned aerial vehicles (UAVs) for surveying marine fauna: a dugong case study. *PLoS ONE* **2013**, *8*, e79556.

Hu, J.H.; Tsai, W.P.; Cheng, S.T.; Chang, F.J. Explore the relationship between fish community and environmental factors by machine learning techniques. *Environ. Res.* **2020**, *184*, 109262.

India State of Forest Report 2019. Available online: https://fsi.nic.in/forest-report (accessed on 15 June 2021).

Joppa, L.N. The case for technology investments in the environment. *Nature* **2017**, *552*, 325.

Kehoe, B.; Patil, S.; Abbeel, P.; Goldberg, K. A survey of research on cloud robotics and automation. *IEEE Trans. Autom. Sci. Eng.* **2015**, *12*, 398–409.

Khaki, M.; Yusoff, I.; Islami, N. Application of the Artificial Neural Network and Neuro-fuzzy System for Assessment of Groundwater Quality. *CLEAN–Soil Air Water* **2015**, *43*, 551–560.

Knudby, A.; Brenning, A.; LeDrew, E. New approaches to modelling fish–habitat relationships. *Ecol. Modelling* **2010**, *221*, 503–511

Kocev, D.; Naumoski, A.; Mitreski, K.; Krstic, S.; Dzeroski, S. Learning habitat models for the diatom community in lake Prespa. *Ecol. Modelling* **2010**, *221*, 330–337.

Kroodsma, D.A.; Mayorga, J.; Hochberg, T.; Miller, N.A.; Boerder, K.; Ferretti, F.; Wilson, A.; Bergman, B.; White, T.D.; Block, B.A.; et al. Tracking the global footprint of fisheries. *Science* **2018**, *359*, 904–908.

Labao, A.B.; Naval, P.C., Jr. Cascaded deep network systems with linked ensemble components for underwater fish detection in the wild. *Ecol. Inform.* **2019**, *52*, 103–121.

Lachkar, Z.; Gruber, N. A comparative study of biological production in eastern boundary upwelling systems using an artificial neural network. *Biogeosciences* **2012**, *9*, 293–308.

Li, R.; Zou, Z.; An, Y. Water quality assessment in Qu River based on fuzzy water pollution index method. *J. Environ. Sci.* **2016**, *50*, 87–92.

Mandal, R.; Connolly, R.M.; Schlacher, T.A.; Stantic, B. Assessing fish abundance from underwater video using deep neural networks. In Proceedings of the 2018 International Joint Conference on Neural Networks (IJCNN), Rio de Janeiro, Brazil, 8–13 July 2018; pp. 1–6.

Marini, S.; Corgnati, L.; Mantovani, C.; Bastianini, M.; Ottaviani, E.; Fanelli, E.; Aguzzi, J.; Griffa, A.; Poulain, P.M. Automated estimate of fish abundance through the autonomous imaging device GUARD1. *Measurement* **2018**, *126*, 72–75.

Mastrorillo, S.; Lek, S.; Dauba, F.; Belaud, A. The use of artificial neural networks to predict the presence of small-bodied fish in a river. *Freshw. Biol.* **1997**, *38,* 237–246.

Mohiuddin, G. Remote Sensing with Computational Intelligence Modelling for Monitoring the Ecosystem State and Hydraulic Pattern in a Constructed Wetland. Master's Thesis, University of Central Florida, Orlando, FL, USA, 2015.

Moitinho-Silva, L.; Steinert, G.; Nielsen, S.; Hardoim, C.C.;;Wu, Y.C.; McCormack, G.P.; López-Legentil, S.; Marchant, R.; Webster, N.; Thomas, T.; et al. Predicting the HMA-LMA status in marine sponges by machine learning. *Front. Microbiol.* **2017**, *8*, 752.

Mosleh, M.A.; Manssor, H.; Malek, S.; Milow, P.; Salleh, A. A preliminary study on automated freshwater algae recognition and classification system. *BMC Bioinform.* **2012**, *13*, S17–S25.

Muñoz-Mas, R.; Martinez-Capel, F.; Alcaraz-Hernández, J.D.; Mouton, A.M. Can multilayer perceptron ensembles model the ecological niche of freshwater fish species? *Ecol. Modelling* **2015**, *309*, 72–81.

Najah, A.; El-Shafie, A.; Karim, O.A.; Jaafar, O.; El-Shafie, A.H. An application of different artificial intelligences techniques for water quality prediction. *Int. J. Phys. Sci.* **2011**, *6*, 5298–5308.

Najah, A.; Elshafie, A.; Karim, O.A.; Jaffar, O. Prediction of Johor River water quality parameters using artificial neural networks. *Eur. J. Sci. Res.* **2009**, *28*, 422–435.

Nunes, J.A.C.; Cruz, I.C.; Nunes, A.; Pinheiro, H.T. Speeding up coral reef conservation with AI-aided automated image analysis. *Nat. Mach. Intell.* **2020**, *2*, 292.

Olaya-Marín, E.J.; Martínez-Capel, F.; Vezza, P. A comparison of artificial neural networks and random forests to predict native fish species richness in Mediterranean rivers. *Knowl. Manag. Aquat. Ecosyst.* **2013**, *409*, 7.

Olden, J.D.; Jackson, D.A. Fish–habitat relationships in lakes: gaining predictive and explanatory insight by using artificial neural networks. *Trans. Am. Fish. Soc.* **2001**, *130*, 878–897.

Palaniswami, M.; Rao, A.S.; Bainbridge, S. Real-time monitoring of the great barrier reef using internet of things with big data analytics. *ITU J. ICT Discov.* **2017,** *1*, 1–10.

Palialexis, A.; Georgakarakos, S.; Karakassis, I.; Lika, K.; Valavanis, V.D. Prediction of marine species distribution from presence–absence acoustic data: comparing the fitting efficiency and the predictive capacity of conventional and novel distribution models. *Hydrobiologia* **2011**, *670*, 241.

Park, Y.S.; Céréghino, R.; Compin, A.; Lek, S. Applications of artificial neural networks for patterning and predicting aquatic insect species richness in running waters. *Ecol. Modelling* **2003**, *160,* 265–280.

Park, Y.S.; Tison, J.; Lek, S.; Giraudel, J.L.; Coste, M.; Delmas, F. Application of a self-organizing map to select representative species in multivariate analysis: a case study determining diatom distribution patterns across France. *Ecol. Inform.* **2006**, *1*, 247–257.

Penczak, T.; Kruk, A.; Galicka, W. Implementation of a self-organizing map for investigation of impoundment impact on fish assemblages in a large, lowland river: Long-term study. *Ecol. Modelling* **2012**, *227*, 64–71.

Pereira, G.C.; Ebecken, N.F. Combining in situ flow cytometry and artificial neural networks for aquatic systems monitoring. *Expert Syst. Appl*. **2011**, *38*, 9626–9632.

Pisupati, B. *Safeguarding India's Biological Diversity: The Biological Diversity Act*; Farmer's Forum. India's Agriculture Magazine: Mumbai, India, 2011.

Pittman, S.J.; Brown, K.A. Multi-scale approach for predicting fish species distributions across coral reef seascapes. *PLoS ONE* **2011**, *6*, e20583.

Rajaee, T.; Khani, S.; Ravansalar, M. Artificial intelligence-based single and hybrid models for prediction of water quality in rivers: A review. *Chemometr. Intell. Lab.* **2020**, *200*, 103978.

Ravindranath, N.H.; Somshekhar, B.S.; Gadgil, M. Carbon flows in Indian forests. *Clim. Chang.* **1997**, *35*, 297–320.

Recknagel, F. ANNA–Artificial Neural Network model for predicting species abundance and succession of blue-green algae. *Hydrobiologia* **1997**, *349*, 47–57.

Russo, T.; Franceschini, S.; D'Andrea, L.; Scardi, M.; Parisi, A.; Cataudella, S. Predicting fishing footprint of trawlers from environmental and fleet data: an application of artificial neural networks. *Front. Mar. Sci.* **2019**, *6*, 670.

Sakizadeh, M. Artificial intelligence for the prediction of water quality index in groundwater systems. *Modeling Earth Syst. Environ.* **2016**, *2*, 8.

Salman, A.; Siddiqui, S.A.; Shafait, F.; Mian, A.; Shortis, M.R.; Khurshid, K.; Ulges, A.; Schwanecke, U. Automatic fish detection in underwater videos by a deep neural network-based hybrid motion learning system. *ICES J. Mar. Sci.* **2020**, *77*, 1295–1307.

Schletterer, M.; Füreder, L.; Kuzovlev, V.V.; Beketov, M.A. Testing the coherence of several macroinvertebrate indices and environmental factors in a large lowland river system (Volga River, Russia). *Ecol. Indic.* **2010**, *10*, 1083–1092.

Sengar, N.; Dutta, M.K.; Sarkar, B. Computer vision based technique for identification of fish quality after pesticide exposure. *Int. J. Food Prop.* **2017**, *20*, 2192–2206.

Sengorur, B.; Koklu, R.; Ates, A. Water quality assessment using artificial intelligence techniques: SOM and ANN—A case study of Melen River Turkey. *Water Qual. Expos. Health* **2015**, *7*, 469–490.

Sharaf El Din, E.; Zhang, Y.; Suliman, A. Mapping concentrations of surface water quality parameters using a novel remote sensing and artificial intelligence framework. *Int. J. Remote Sens.* **2017**, *38*, 1023–1042.

Sharma, V.; Chaudhry, S. An overview of Indian forestry sector with REDD. *Int. Sch. Res. Not.* **2013**, *2013*, 298735.

Siddiqui, S.A.; Salman, A.; Malik, M.I.; Shafait, F.; Mian, A.; Shortis, M.R.; Harvey, E.S. Automatic fish species classification in underwater videos: exploiting pre-trained deep neural network models to compensate for limited labelled data. *ICES J. Mar. Sci.* **2018**, *75*, 374–389.

Singh, K.P.; Gupta, S.; Rai, P. Predicting acute aquatic toxicity of structurally diverse chemicals in fish using artificial intelligence approaches. *Ecotoxicol. Environ. Saf.* **2013**, *95*, 221–233.

Sinha, B.; Kala, C.P.; Katiyar, A.S. *Enhancing Livelihoods of Forest Dependent Communities through Synergizing FDA Activities with Other Development Programs*; RCNAEB Sponsored Project; Indian Institute of Forest Management (IIFM): Bhopal, India, 2010.

Song, H.; Xu, F.; Zheng, B.; Xiang, Y.; Yang, J.; An, X. An artificial intelligence recognition algorithm for Yangtze finless porpoise. In Proceedings of the OCEANS 2015—MTS/IEEE Washington, Washington, DC, USA, 19–22 October 2015; pp. 1–6.

Strobl, R.O.; Robillard, P.D. Artificial intelligence technologies in surface water quality monitoring. *Water Int.* **2006**, *31*, 198–209.

Tang, M.; Jiao, Y.; Jones, J.W. A hierarchical Bayesian approach for estimating freshwater mussel growth based on tag-recapture data. *Fish. Res.* **2014**, *149*, 24–32.

Toro, C.H.F.; Meire, S.G.; Gálvez, J.F.; Fdez-Riverola, F. A hybrid artificial intelligence model for river flow forecasting. *Appl. Soft. Comput*. **2013**, *13,* 3449–3458.

Tsai, W.P.; Huang, S.P.; Cheng, S.T.; Shao, K.T.; Chang, F.J. A data-mining framework for exploring the multi-relation between fish species and water quality through self-organizing map. *Sci. Total Environ.* **2017**, *579*, 474–483.

Tung, T.M.; Yaseen, Z.M. A survey on river water quality modelling using artificial intelligence models: 2000–2020. *J. Hydrol.* **2020**, *585*, 124670.
Villon, S.; Mouillot, D.; Chaumont, M.; Darling, E.S.; Subsol, G.; Claverie, T.; Villéger, S. A deep learning method for accurate and fast identification of coral reef fishes in underwater images. *Ecol. Inform.* **2018**, *48*, 238–244.
Volf, G.; Atanasova, N.; Kompare, B.; Precali, R.; Oani, N. Descriptive and prediction models of phytoplankton in the northern adriatic. *Ecol. Modelling* **2011**, *222*, 2502–2511.
Wang, P.; Yao, J.; Wang, G.; Hao, F.; Shrestha, S.; Xue, B.; Xie, G.; Peng, Y. Exploring the application of artificial intelligence technology for identification of water pollution characteristics and tracing the source of water quality pollutants. *Sci. Total Environ.* **2019**, *693*, 133440.
Watts, M.J.; Li, Y.; Russell, B.D.; Mellin, C.; Connell, S.D.; Fordham, D.A.; A novel method for mapping reefs and subtidal rocky habitats using artificial neural networks. *Ecol. Modelling* **2011**, *222*, 2606–2614.
Xia, C.; Fu, L.; Liu, Z.; Liu, H.; Chen, L.; Liu, Y. Aquatic toxic analysis by monitoring fish behavior using computer vision: A recent progress. *J. Toxicol.* **2018**, *2018*, 2591924.
Xu, L.; Bennamoun, M.; An, S.; Sohel, F.; Boussaid, F. Deep learning for marine species recognition. In *Handbook of Deep Learning Applications*; Springer: Cham, Switzerland, 2019; pp. 129–145. https://doi.org/10.1007/978-3-030-11479-4_7.
Yaseen, Z.M.; Kisi, O.; Demir, V. Enhancing long-term streamflow forecasting and predicting using periodicity data component: application of artificial intelligence. *Water Resour. Manag.* **2016**, *30*, 4125–4151.
Yoo, J.W.; Lee, Y.W.; Lee, C.G.; Kim, C.S. Effective prediction of biodiversity in tidal flat habitats using an artificial neural network. *Mar. Environ. Res.* **2013**, *83*, 1–9.
Zarkami, R.; Sadeghi, R.; Goethals, P. Use of fish distribution modelling for river management. *Ecol. Modelling* **2012**, *230*, 44–49.
Zhu, X.; Li, D.; He, D.; Wang, J.; Ma, D.; Li, F. A remote wireless system for water quality online monitoring in intensive fish culture. *Comput. Electron. Agric.* **2010**, *71*, S3–S9.