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SHORT COMMUNICATION

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The slow rise of technology: Computer vision techniques in fish population connectivity

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Abstract

1. Technological advancements in data collection and analysis are producing a new generation of ecological data. Among these, computer vision (CV) has received increased attention for its robust capabilities for rapidly processing large volumes of digital imagery.
2. In marine ecosystems, the study of fish connectivity provides fundamental information for assessing fisheries stocks, designing and implementing protected areas and understanding the impact of habitat loss. While the field of fish connectivity has benefited from technological advancements, the extent to which novel techniques, such as CV, have been utilized has not been assessed. To inform future directions and developments, this study reviewed the current use of CV in fish connectivity research, quantified how the implementation of such technology in fish connectivity research compared with other areas of marine research and described how this field could benefit from CV.
3. The review found that the use of remote camera systems in fish connectivity research is increasing, but the implementation of automated analysis of digital imagery has been slow. Successful implementation and expansion of CV frameworks in aquaculture and coral reef ecology suggest that CV techniques could greatly benefit fish connectivity research.
4. A case study of potential use of CV in fish connectivity research, scaling up optimal foraging models to predict marine population connectivity, highlights how beneficial it could be.
5. The capacity for CV techniques to be adopted alongside traditional approaches, the unparalleled speed, accuracy and reliability of these approaches and the benefits of being able to study ecosystems along multiple spatial–temporal scales, all make CV a valuable tool for assessing connectivity. Ultimately, these technologies can assist data-driven decisions that directly influence the health and productivity of marine ecosystems.

KEYWORDS
artificial intelligence, behavioural ecology, deep learning, dispersal, environmental monitoring, machine learning, new techniques, operational maturity analysis, research trends, underwater video

1 | INTRODUCTION

Technological advancements are allowing the collection of a 'new generation of ecological data' (Allan et al., 2018). Among new technologies, computer vision (CV), defined as the scientific field that explores the use of computers to interpret digital images or videos, has gained much attention given that remote video-based approaches have become more common for monitoring ecosystems (Waldchen & Mader, 2018). Remote camera imagery (e.g. underwater stereography or baited underwater stations) can monitor individuals and populations at different spatial and temporal resolutions (Bicknell, Godley, Sheehan, Votier, & Witt, 2016; Mallet & Pelletier, 2014). Automatic analysis of images has become more accurate and rapid as advancements in deep learning models, a subset of machine learning algorithms, have enhanced the capacity of CV to extract and classify features. The power of CV as a data collection tool and the varied capabilities as a post-processing tool is seeing this technique used across a variety of scientific research areas (Aguzzi et al., 2019; Weinstein, 2018). More importantly, CV is capable of generating large amounts of data that can be used to reveal intricate patterns, trends and associations (Waldchen & Mader, 2018). For example, Ocean Networks Canada are using CV-powered cable observatories and interactive sensors to monitor deep-sea ecosystems (Aguzzi et al., 2019).

Marine population connectivity, described as the study of the exchange of individuals among populations (Bryan-Brown, Brown, Hughes, & Connolly, 2017; Cowen, Gawarkiewicz, Pineda, Thorrold, & Werner, 2007), shapes predator–prey dynamics, nutrient dynamics and trophic functions (Olds et al., 2018). For example, high levels of connectivity between seagrass and coral reefs by herbivorous fish improve ecological health by preventing both ecosystems from being overgrown by algae (Pagès, Gera, Romero, & Alcoverro, 2014). Knowledge of animal connectivity is also fundamental to many research objectives in marine science, including for the design of marine protected area networks (Calò et al., 2013), the understanding of recovery rates of ecosystems following disturbances (Cumming, 2011) and the management of fisheries (Fogarty & Botsford, 2007). Studying marine population connectivity requires large volumes of data because animal movement covers different magnitudes, directions and spatial levels of ecological organization (Olds et al., 2018). Commonly used techniques, such as in-water diver assessments and netting and trawling, have limited spatial and temporal capabilities which can make data collection very costly and demanding. The use of novel techniques such as CV, machine learning and deep learning algorithms, along with the application of learning paradigms (i.e. supervised, unsupervised and reinforcement learning), is particularly suited to the subfield of marine population connectivity because it can capture, learn and process complex data that then can help to measure marine population connectivity (Olds et al., 2018).

This study builds on the review by Bryan-Brown et al. (2017), who showcased the 'what?' and 'how?' of marine population connectivity research. Bryan-Brown et al. (2017) found that technological innovations contributed to a surge in research on marine population connectivity. However, whether CV techniques are being broadly used to study marine population connectivity remains mostly unexplored (Pittman, 2018). To inform future directions and developments, this study reviewed the implementation of CV in the field of marine population connectivity. This study focused on fish population connectivity across the four most studied habitats in marine population connectivity literature (Bryan-Brown et al., 2017). Both ray-finned fishes (Class Actinopterygii), the most studied animal group (Bryan-Brown et al., 2017), and cartilaginous fishes (Class Chondrichthyes) were reviewed owing to their ecological and economic importance as fisheries target species.

Assessing existing methods provides a solid basis for considering future directions and developments (Snaddon, Petrokofsky, Jepson, & Willis, 2013). The current study aimed to answer three key questions: (1) are CV techniques being used in fish connectivity studies; (2) are there any lessons regarding CV uptake in other areas of marine research that can be transferred to the study of fish connectivity; and (3) how can CV techniques benefit fish connectivity research? This study addressed the first two questions with a literature review. Then, examples from the literature were drawn upon to highlight how CV techniques could benefit connectivity research, and a case study was used to illustrate a real-world application. Ultimately, this study aimed to provide a current technology base of fish connectivity research to inform scientists and managers about the areas where innovations have or could occur.

2 | METHODS

To quantify the level of implementation and maturity of technological advancements in the marine fish connectivity literature, a library of potentially suitable studies was created by searching the Web of Science (https://www.webofknowledge.com/) and Scopus (https://www.scopus.com/) online databases (1990 to May 2019). The search terms utilized by Bryan-Brown et al. (2017) were used as this study represents the most recent and robust assessment of marine population connectivity research effort. The four most studied ecosystems (coral reef, seagrass, algal bed and mangrove habitats) in the marine population connectivity literature were selected as focal habitats in this study (Bryan-Brown et al., 2017). The search incorporated terms related to marine studies, bony and cartilaginous fish, and different variations for 'connectivity' (migration, dispersal, recruitment, linkage). For full details of the search terms, data extraction methodology and resulting database see Appendix S1. The final dataset comprised 361 studies. From these studies, the following parameters were documented: (1) the technique used to measure fish connectivity; (2) the use of any post-processing technique; and (3) the focal habitat in which the data collection technique was employed. The various data collection techniques were then divided into those that involved capturing and processing digital images or videos ('computer vision techniques') and those that did not ('traditional techniques'; Table 1). For full details of technique classification and definition see Appendix S1. An operational maturity analysis was conducted to provide a clear picture of how well-developed each technique, programme or method is

TABLE 1 Operational maturity assessment of traditional and computer vision (CV) techniques used to measure fish connectivity in four marine habitats (seagrass, mangroves, coral reefs and algal beds)

Technique	Traditional techniques							Computer vision techniques						
		In-water diver assessments						Underwater video stations		In-water diver assessments		Underwater vehicles		
Data collection method								Photo/Video		Photo/Video		Photo/Video		
Post processing technology	Netting and Trawl	Visual	Statistical modelling	Tagging Telemetry	GIS	Isotope	Genetic	Manual Human	Machine learning	Manual Human	Machine learning	Manual Human	Machine learning	
Seagrass	27	45	9	10	16	21	2	11		1				
Mangroves	23	38	14	11	17	21		9						
Coral reefs	61	95	71	20	32	33	108	10		1		2		
Algal beds	8	14	5	5	3	6	6	3		2				
Total	119	192	99	46	68	81	116	33	0	4	0	2	0	**760**

Matured: The technique has sufficient evidence and has been implemented successfully in ≥20 peer-reviewed studies	**Maturing**: The technique has sufficient evidence and has been implemented successfully in ≥5 but <20 peer-reviewed studies	**Developing**: The technique has some research evidence and has been implemented successfully in ≥1 but <5 peer-reviewed studies	**Absent**: The technique has not been used or documented in the fish connectivity literature

Note: Numbers in each cell represent the total count of studies using that technique successfully to measure fish movement. Note that the sum of row totals is greater than the total number of studies included in the review because several studies measured connectivity across multiple habitats or used more than one technique. This review found no studies using non-CV novel techniques (e.g. environmental DNA) to measure fish connectivity in focal habitats.

in fish connectivity research. Briefly, an operational maturity analysis involves assessing technological innovations and assigning a maturity level (Becker, Knackstedt, & Pöppelbuß, 2009; García-Mireles, Ángeles Moraga, & García, 2012; Santos-Neto & Costa, 2019). Finally, to assess how the marine fish connectivity literature compares with other areas of marine research in terms of its use of CV techniques, a similar search was conducted but tailored to the fields of aquaculture and coral reef ecology (see Appendix S2 for full details). From these libraries, the number of studies that utilized digital imagery and CV techniques were quantified.

3 | RESULTS

Traditional techniques such as visual surveys (192), netting and trawling (119) and genetic analyses (116) have been widely used in fish connectivity research (Table 1). Even in recent years, traditional techniques are still far more common than CV techniques (Figure 1) (see Appendix S3). The relative frequency of occurrence of each technique differed greatly depending on the focal habitat (Table 1). For example, of the 116 studies using genetic techniques to assess population connectivity, 108 (93%) were conducted on coral reefs.

The use of digital camera systems is maturing in most habitats. For instance, combined, underwater video stations (33), camera-equipped in-water diver assessments (4) and underwater vehicles equipped with photo or video devices (2) span the four focal habitats (Table 1). However, none of the studies that utilized digital cameras used CV to extract useable information, instead relying on manual processing.

Although novel, non-CV techniques (e.g. environmental DNA) offer a way to sample the movement and connectivity of genetic material non-invasively (Adams et al., 2019), no studies were identified that used these methods to measure fish connectivity in the focal habitats.

4 | DISCUSSION

4.1 | Lessons from CV implementation in other marine research areas

Other research areas in marine science such as coral reef ecology and aquaculture have long been using digital imagery and CV techniques, (Langenkämper, Zurowietz, Schoening, & Nattkemper, 2017) with use steadily increasing since the late 1990s (Figure 2). Conversely, consistent use of digital imagery only appeared in fish connectivity studies within the last five years (Figure 2). In coral reef ecology, the use of CV centres around the automatic identification of fish (Villon et al., 2018), algae, coral and invertebrates (Beijbom et al., 2015;

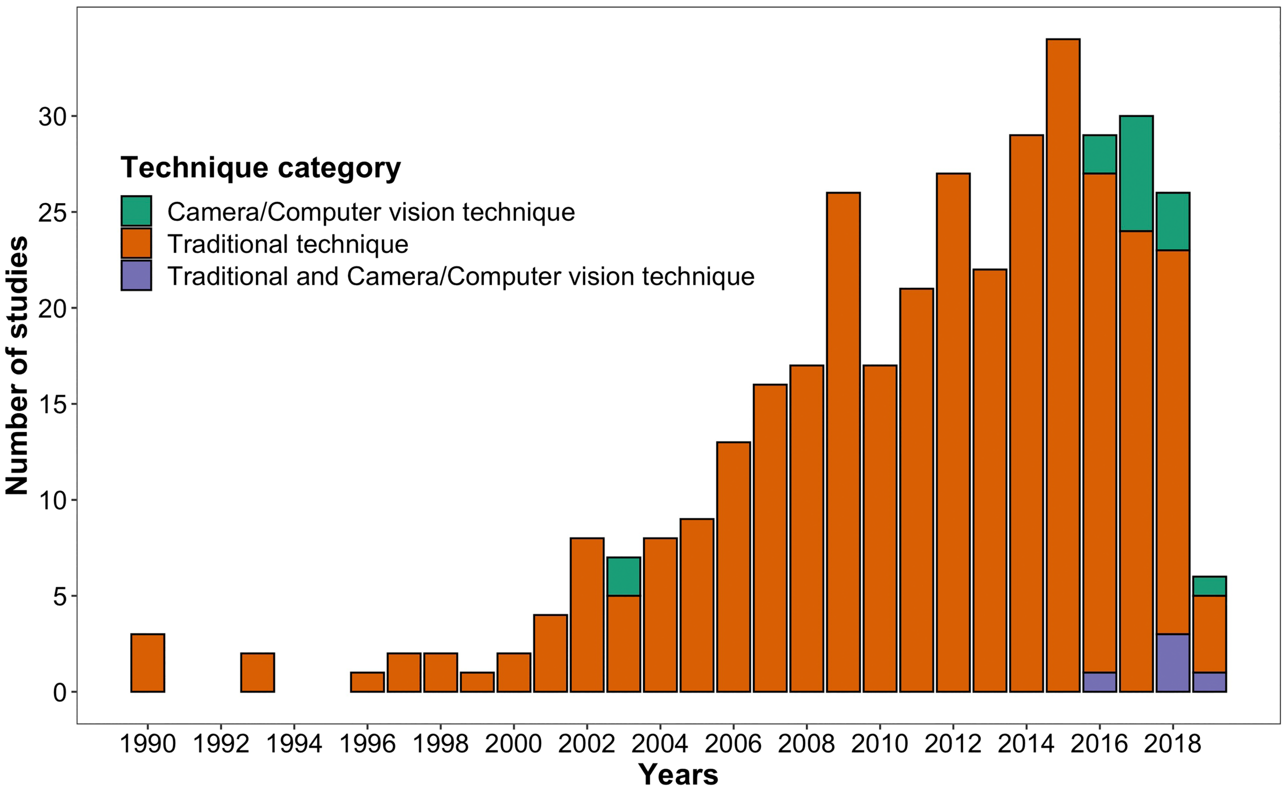

FIGURE 1 Absolute number of fish connectivity studies in four focal habitats (seagrass, mangroves, coral reefs and algae beds) published per year, split into three technique categories. Camera/computer vision techniques included all studies that used camera imagery to study aspects of fish connectivity. Traditional techniques included studies that used netting, trawling, visual in-water diver assessments, statistical modelling, tagging and telemetry, GIS and genetic methodologies. The final category is for studies that used a combination of camera/computer vision and traditional techniques

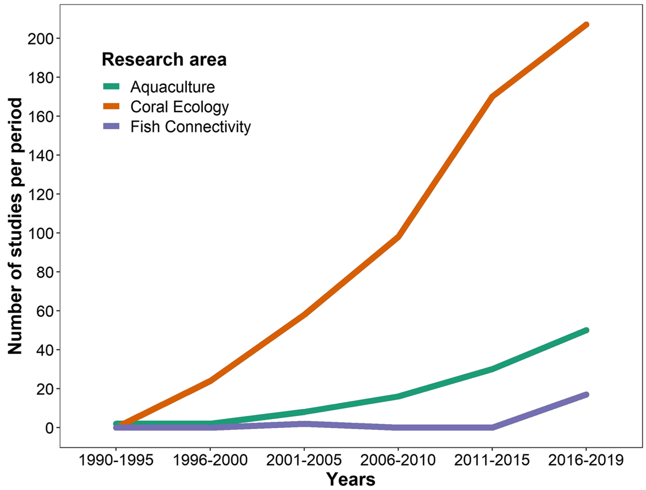

FIGURE 2 Absolute number of studies using underwater cameras, computer vision technologies, deep learning techniques and machine learning algorithms in aquaculture, coral reef ecology and fish connectivity research from 1990 to May 2019. Data shown in 5-yearly bins to aid visualization

González-Rivero et al., 2020). Open-source platforms for the annotation of underwater images and automatic identification of marine biota such as Catami (catami.org) (Althaus et al., 2015), Squidle+ (squidle.org), BIIGLE 2.0 (biigle.de) (Langenkämper et al., 2017), BenthoBox (benthobox.com) and CoralNet (coralnet.ucsd.edu) (Beijbom et al., 2015), have also enhanced the uptake of novel CV techniques in coral reef ecology. In aquaculture, digital imagery and CV techniques have been successfully used to monitor feeding activity and determine harvesting times (Costa, Loy, Cataudella, Davis, & Scardi, 2006; Lee, Kang, & Lim, 2014), document fish behaviour and movement (Pinkiewicz, Purser, & Williams, 2011; Stien, Bratland, Austevoll, Oppedal, & Kristiansen, 2007), count lice, estimate biomass, assess appetite levels and optimize feeding (see AquaByte, aquabyte.no). Autonomous underwater robots using novel artificial intelligence algorithms are also becoming more reliable and robust for monitoring fish health in open-pen sea cages (see Deep Trekker, deeptrekker.com) (Saberioon, Gholizadeh, Cisar, Pautsina, & Urban, 2017). The development and application of CV in the fields of coral reef ecology and aquaculture have allowed for more robust and automatic monitoring of animals in different and complex ecosystems. The diverse ways in which these two fields have adopted and implemented CV provide clear evidence for the potential applications and benefits of utilizing CV in the study of fish connectivity, and the relative ease at which methods can be transferred across research areas.

4.2 | Benefits of CV to fish connectivity research

Most areas of marine science would benefit from more remote and automatic techniques to collect and analyse data, and fish connectivity is no exception (Figure 3). CV techniques allow the collection of extensive spatial and temporal data at high resolutions; something that is difficult and costly using traditional, manual techniques. This study suggests that CV techniques can benefit fish connectivity research in two key ways: (1) by complementing traditional techniques; and (2) by producing rapid, automatic and consistent high-quality datasets.

4.2.1 | Complementing traditional data collection techniques

A key benefit that CV provides to science is that it can complement traditional techniques. For example, in-water diver assessments are

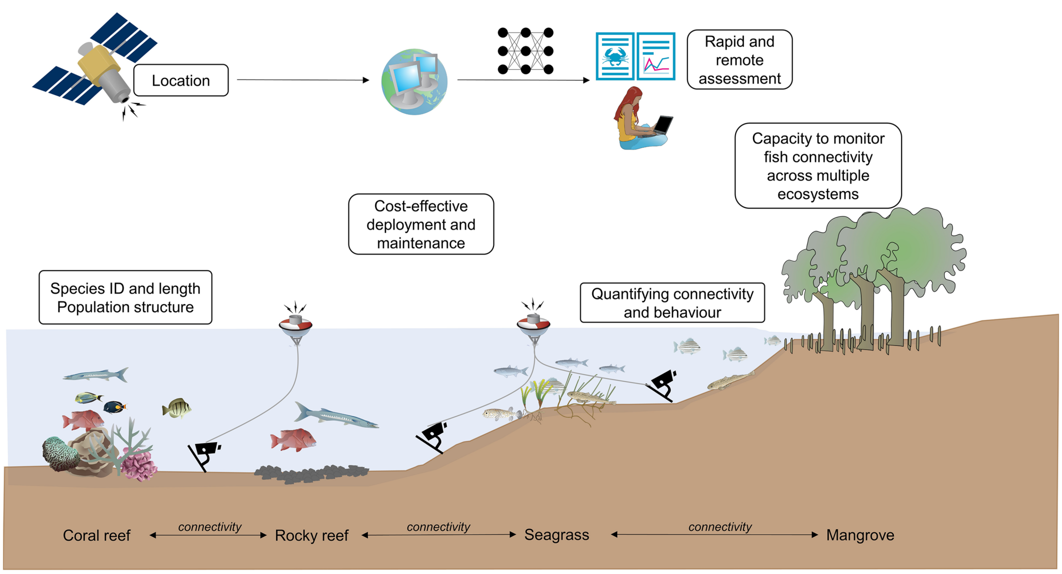

FIGURE 3 Schematic diagram illustrating the many advantages of computer vision techniques and parameters that can be measured to enhance the study of fish connectivity. The ecological data collected by underwater camera stations in this example can be collected across multiple ecosystems and transmitted to computers through satellites to be quickly processed for rapid and remote assessments of connectivity. Symbols courtesy of ian.umces.edu/symbols/

among the most commonly used techniques to explore fish connectivity, but divers have limited temporal and spatial capabilities, resulting in a 'restricted' view of the ecosystem. CV can complement visual assessments because cameras can be deployed at many sites and cover larger spatial scales than typical diver-based assessments. This can increase the spatial and temporal scope of monitoring. Nevertheless, there are ecological parameters, such as the identification and classification of complex predatory interactions or the accurate identification of morphologically similar but taxonomically different species, which are highly complex to measure using CV but which can be relatively easily collected and analysed by divers. Alternatively, CV can power the navigation of autonomous robots designed for sample collection of marine environmental DNA in marine ecosystems (Yamahara et al., 2019).

4.2.2 | Rapid, automatic and consistent, high-quality datasets

Increased availability of high-quality data can lead to statistical models with greater power to inform management actions, but these high-quality datasets are difficult to produce. Post-processing using machine learning can overcome the issues and costs of analysing large datasets because it is rapid and accurate, and the processing can be automated. For example, machines can process and classify underwater fish imagery 40× faster than human experts and citizen scientists (Ditria et al., 2020). The error rates of deep learning algorithms continue to decline, making them reliable tools for scientific studies (Waldchen & Mader, 2018). In fact, current deep learning algorithms can extract information from digital data more consistently than human experts (Villon et al., 2018). Additionally, with advancements in telecommunication, non-destructive and long-term underwater observation of fish assemblages with CV integration is now possible (Marini et al., 2018).

Machine learning post-processing and CV can also aid in the analysis of historical digital datasets from existing long-term monitoring programmes (Williams et al., 2019). A recent study showcased that, through complex statistical models, integration of manually (citizen science/experts) and automatically (machine learning) classified image-based data from different long-term monitoring programmes is possible (Peterson et al., 2019). This novel approach of integrating disparate datasets can be used to inform conservation and management actions through data-driven decisions. Additionally, the analysis of historical datasets could benefit from methodologies based on transfer learning, where historical data are transferred for training machine learning-based classifiers (Weiss, Khoshgoftaar, & Wang, 2016).

4.3 | Case study: Linking population connectivity to behavioural ecology

Population connectivity is an emergent property of individual fish behaviour. Individual behaviour may, therefore, predict connectivity patterns, but the link between individual behaviour and population level patterns is poorly known (Nabe-Nielsen, Tougaard, Teilmann, Lucke, & Forchhammer, 2013). Filling this gap requires datasets that capture movement at both individual and population scales. By increasing our observational capacity, CV techniques may be able to fill this data gap. For instance, herbivorous fish can trade-off predation risk against access to food, leading to patterns of overgrazing near refuge habitats (Downie, Babcock, Thomson, & Vanderklift, 2013). Thus, models of individual foraging decisions, which have over half a century of development (Craig & Crowder, 2000), could be used to predict cross-habitat connectivity and its effect on ecological functions. CV datasets, which can measure the movement of large numbers of individuals across habitats, could provide sufficient data to make an empirical test of how behavioural models can be scaled up to the population level.

4.4 | Considerations of adopting CV techniques

Although CV can provide fast and high-quality datasets and assist in post-processing, developing CV models requires advanced knowledge of programming environments such as Anaconda (anaconda.com) and Jupyter (jupyter.org). The cost of obtaining accurate and transferrable models is also an important consideration. Training, testing and running predictions on servers can be expensive, but grant programmes such as Microsoft AI for Earth (https://www.microsoft.com/en-us/ai/ai-for-earth) provide support to projects that use artificial intelligence. Further, opportunities through data mining and digital libraries are solving many of the challenges of training data needs. With ongoing developments in CV and increased accessibility to data, it is expected that costs will decrease significantly. Despite the initial costs, investments in CV often become cost-effective in the long term, especially when processes become automated and the time needed and cost of labour decreases.

4.5 | Conclusions

Remote camera systems and CV techniques can help provide robust, reliable and automatic tools to monitor and observe fish connectivity in marine ecosystems. Technological advancements have allowed us to understand the complexities of animal population connectivity better, and this study clearly shows that these techniques have been adopted in other similar fields for decades and continue to be adopted at increasing rates. Fish connectivity research has been comparatively slow to embrace CV techniques. Conventional techniques are still more common than CV techniques, possibly because of a perceived need for increased development time and funding to realize the latter. In general, CV techniques are best viewed as complementary to traditional techniques, rather than a replacement. Although many CV techniques require high initial investment, they can provide exponential returns over time, and once the application is running, techniques can be adapted to novel situations quickly and cheaply. Ultimately, the capacity for CV to be adopted alongside traditional approaches, the unparalleled speed, accuracy and reliability of these approaches, and the benefits of being able to study ecosystems over multiple scales make CV a valuable tool to assess connectivity. CV thus has the capacity to inform data-driven decisions that directly influence the health and productivity of marine ecosystems.

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of this article.

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