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Tools and Technology

Potential Applications of Wireless Sensor Networks for Wildlife Trapping and Monitoring Programs

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ABSTRACT There are notable costs in maintaining a wildlife trapping program, primarily labor and travel costs associated with frequently and regularly checking large numbers of traps. Wireless sensor networks have the potential to significantly decrease operational costs of terrestrial wildlife trapping and monitoring programs, particularly those involving labor-intensive live-trapping. Furthermore, sensor networks can collect, transmit, and store vast volumes of environmental data, which may be used in research or to refine wildlife management or monitoring. In a modeled example, we estimated that operational cost savings of up to 70% could accrue from use of wireless sensor networks. Cost savings were greater when more traps were included in the network, but declined as rates of sprung traps increased. A simple benefit–cost analysis suggested that use of wireless sensor networks is justifiable economically, although widespread use may be constrained by legislative or regulatory requirements for field staff to service or check traps or the need to replace bait. Should increasing use reduce hardware costs, this technology has great potential for reducing costs of trap-based control programs and increasing the quantity and quality of data from wildlife monitoring studies.

KEY WORDS benefit–cost analysis, operational costs, remote sensing, wildlife trapping, wireless sensor networks.

Terrestrial wildlife management frequently involves the use of trapping to control vertebrate pests, estimate population parameters, or monitor individual behavior patterns. Although this is the most appropriate methodology in many cases, such as where a single species is targeted or where the target species occurs at low densities (Goodrich et al. 2001), there are notable costs associated with maintaining a trapping program. Depending on the aims of the program and legislative requirements, traps need to be checked frequently and regularly, as often as daily in live-capture studies. Kill traps may be checked less frequently. Trap checking involves a considerable investment of resources, primarily in terms of labor and travel costs, because trap-lines or networks often extend over many kilometers of animal habitat, much of which may not have vehicle tracks (Darrow and Shivik 2008).

In New Zealand, for example, multiple indigenous species are threatened by introduced mammalian predators, including feral cats (*Felis catus*), mustelids (*Mustela* spp.), rats (*Rattus* spp.), and European hedgehogs (*Erinaceous europaeus*), all of which are widespread and abundant (see King [2005] for species-specific information). Much of the control of these species uses landscape-scale trapping programs on government-managed and other conservation land tenures. In addition to their control, research aimed at estimating species densities or investigating their ecology often uses live-trapping programs to obtain animals for study. Much of the cost of running trapping programs is from the labor, because checking trap-lines is time-consuming. Although kill-trap service intervals are determined primarily by bait longevity and may range from weekly to monthly depending on environmental conditions, live-trapping places the highest demands on program resources because traps need to be checked at least once daily. In such programs, time and money may be used inefficiently in carrying out daily inspections of large numbers of empty traps.

In live-capture trapping programs, it is important for welfare reasons to minimize the period animals are held in traps. Trapped animals may be at risk of stress, hypo- and hyperthermia, dehydration and injury, either from the trap or from other animals (Larkin et al. 2003, Ó Néill et al. 2007, Johansson et al. 2011). It is also beneficial to minimize the frequency of human disturbance of the trap site, which might induce trap-shyness in animals responsive to signs left after visits (Marks 1996).

Since the early 1980s, researchers have examined how remote monitoring of traps and other detection devices might minimize both program resource costs (Gebhardt

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et al. 2009) and the time for which an animal is held captive (Larkin et al. 2003). Early efforts used trip-switches to activate, deactivate, or change the pulse rate of modified very-high-frequency (VHF) telemetry transmitters when a trap or other device was triggered (Hayes 1982, Nolan et al. 1984, Marks 1996). Subsequent modifications included the use of mobile-phone-based applications as trap alarms with the aim of reducing injuries to animals caught in leg-hold traps (Larkin et al. 2003, Ó Néill et al. 2007). Remote monitoring systems may be limited by poor or absent Global System for Mobile Communications coverage in a trapping area or from topographical barriers to VHF signal transmissions in radio-based systems. In VHF systems, these can be overcome to some extent by increasing the height at which transmitting antennae are deployed and by including an intermediate relay station between trap-linked transmitters and the receiver (Benevides et al. 2008, Johansson et al. 2011).

The natural progression from a single relay station passing on data from an array of devices is to link multiple relay points, each with its own detection array, to increase a monitoring system's scope. This is, essentially, the concept behind wireless sensor networks (WSNs). A WSN consists of devices that detect and measure environmental variables (the sensors), and a way for those sensors to communicate data to each other and/or back to a base station wirelessly (the network). Sensors are designed to produce an electrical signal in response to environmental changes (e.g., temperature, humidity, precipitation, wind, soil moisture, or ground- and stream-water levels); and chemical, audio, or mechanical cues (Porter et al. 2005). A typical sensor consists of a transducer, which responds to the environment, coupled with a means of converting the analogue transducer response to digital format, a processor, and a radiotransmitter. Sensors range in size from tiny "motes" to larger complex sampling systems (Porter et al. 2012). A unit that includes one or more sensors and a wireless transmitting component is commonly referred to as a node. The processor component also allows nodes to store data and communicate with other nodes in the network. This ability for nodes to communicate with each other has multiple benefits: the network can be "self-healing" in that, should one node fail, an alternative data transfer pathway is utilized. Nodes also can be "retasked" *in situ*, for example, if a threshold environmental change is detected, data collection protocols can be modified accordingly, and data from various nodes, or localized clusters of nodes, can be aggregated automatically in various configurations (Mainwaring et al. 2002).

Wireless sensor networks can be established in a range of configurations including a "mesh network," whereby each node communicates with a number of other nodes to pass data on, so not all nodes need to be in range of a receiving base station. Larger, more complex networks can be set up with spatially localized clusters of sensor nodes (Fig. 1). Each node in the cluster communicates directly, or via multiple inter-node "hops," with its own more powerful transmitting station or "gateway," each of which then sends data from its clusters to the main base station (e.g., Szewczyk et al. 2004*b*). Networks can also be set up as chains, or even as conventional "hub and spoke" networks, where each node communicates with a base station. Base stations may simply store data from the WSN for later retrieval, or have high-powered transmitters (such as a large radio aerial), a satellite link, or even a fixed line connection, to send the data back to a field office. Wireless sensor nodes may even be configured to transmit data to a handheld device when the device is carried close enough to the node (effectively a roaming base station) or to a civilian aircraft (e.g., http://nationalzoo si.edu/scbi/partnersinthesky/; accessed 16 Jul 2014).

With the ability to monitor at a greater spatial scale and greater frequency than more established monitoring systems, WSNs have been deployed in a range of environmental studies including simultaneous large-scale lake monitoring in China and the United States (Porter et al. 2005); monitoring local environments around rare plants in Hawaii, USA (Martincic and Schwiebert 2005); and for collecting data on environmental conditions, tree growth, and bio-acoustic wildlife monitoring (Springbrook National Park, Queensland, Australia; http://www.csiro.au/en/Outcomes/ICT-and-Services/National-Challenges/rainforest-rehabilitation.aspx, accessed 10 Jul 2014). Wildlife management applications include the use of tiny sensors (or motes), both in seabird breeding burrows and the surrounding environment in an attempt to monitor incubation behavior of Leach's storm petrels (*Oceanodroma leucorhoa*) on Great Duck Island, Maine, USA. Small changes in nest temperature were used to indicate the presence of birds in a system that covered multiple patches of burrows, by means of clusters of nodes connected to a base station by multiple gateways (Mainwaring et al. 2002, Szewczyk et al. 2004*a*). Juang et al. (2002) described the development of a mobile network to monitor movements of zebra (*Equus grevyi* and *E. burchelli*) in Kenya by using collar-mounted sensors that employed global positioning system technology and peer-to-peer routing of data to overcome difficulties of monitoring mobile animals over large areas without Global System for Mobile Communications or other communication coverage.

Our goals were to 1) consider how the use of WSN in live-trapping networks might reduce operational costs and shorten animal holding times by focusing effort only on those traps reported as sprung and 2) develop a simple benefit–cost model as a heuristic example of how the relative costs and savings can be compared. We did this using real-world data on WSN establishment costs and operational costs and trap-spring rates from a live-trapping program in New Zealand's South Island.

METHODS

Estimating Operational Cost Savings in Trapping Programs

As a heuristic example, we used a simple spreadsheet model to estimate potential cost savings from using wireless sensors in a WSN to indicate sprung traps. We applied a modified version of the approach of Gebhardt et al. (2009), who considered the operational cost savings when use of a

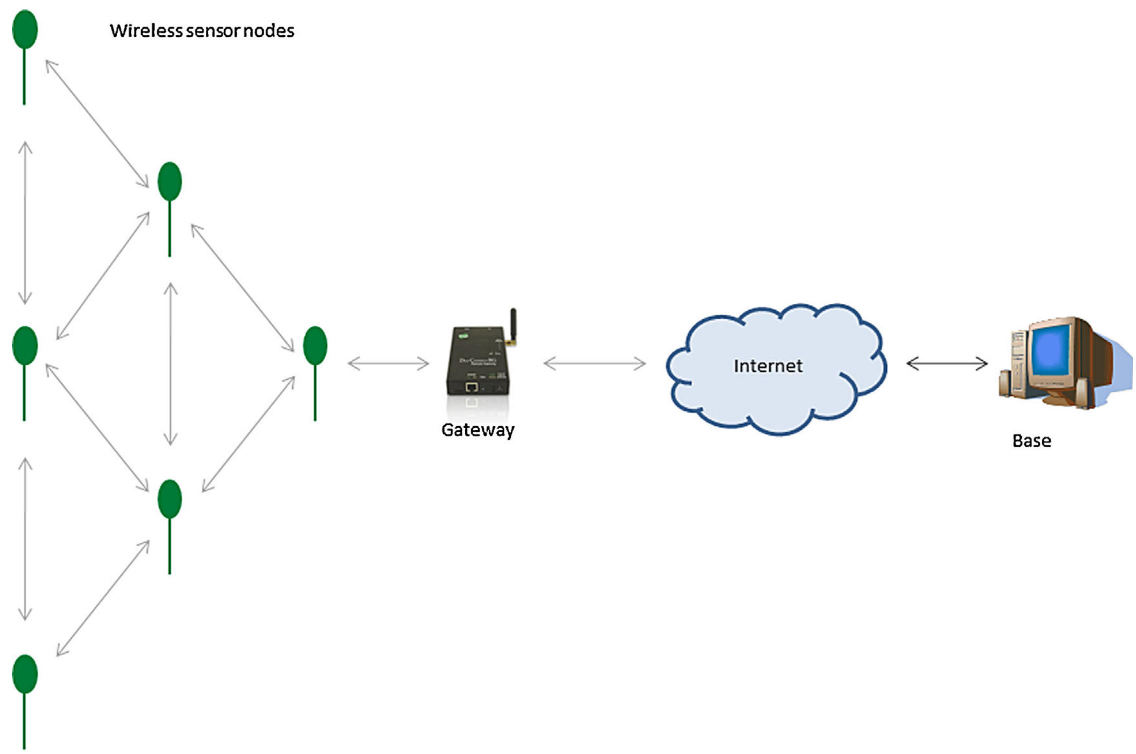

Figure 1. Schematic representation of a simple wireless sensor network to monitor environmental variables. Sensor nodes collect data on environmental variables and all nodes both communicate with each other and transmit data back to researchers via a more powerful gateway or "base-station," which transmits either using internet or satellite technology. The system can be adapted via information sent from the client in the opposite direction.

WSN reduced the need for field staff to frequently visit every trap in a trapping network. We estimated the relative operational costs for 2 sizes of live-trapping network (150 and 300 traps) under 3 scenarios: 1) daily visits to every trap by a trapper; 2) visits to only those traps detected as sprung by a WSN; 3) and use of a WSN, but with a preset 5-day interval rebaiting and servicing schedule. We only estimated costs for a live-trapping program, but the process could equally be applied to kill-traps if traps needed to be visited more frequently than the interval dictated by bait longevity, such as when traps become saturated during periods of higher trap-rates of the target species because of seasonal changes in abundance or foraging behavior. Scenarios modeled were typical of trapping operations currently carried out by the New Zealand Department of Conservation.

We first constructed a simple deterministic spreadsheet-based model of the operational cost components incurred when a trapper travels from a base to the start of a trapping network and then travels around the network by vehicle and checks each trap daily for 10 consecutive days every month. Sprung traps incur a greater time cost to check than unsprung traps because of the need to process trapped animals or to reset sprung, but empty traps. At the end of the network, the trapper travels back to base. To simulate a realistic distribution of daily numbers of sprung and unsprung traps in the network we used a random integer-selection function constrained so that simulated 10-day sprung trap-rates matched up with mean monthly trap-rates from a real-world predator trapping program in the South Island of New Zealand, where traps were also set for 10 days every month (Department of Conservation, unpublished data, 2006–2011).

We assumed that the 20 km drive from the base to the start of the network took 15 min and the drive around the network was 15 km long for the 150-trap network and twice that for the larger network. The trapper could travel at 8 km/hr around the network by all-terrain vehicle and the time taken to check each trap was 1 or 6 min for unsprung and sprung traps, respectively. We further assumed a labor rate of $20.00/hr (New Zealand currency, 2015 benchmark) based on current salary information for an experienced Department of Conservation ranger (http://www.careers.govt.nz/jobs/conservation/ranger/about-the-job; accessed 27 Jan 2015) and a vehicle running cost of $0.75/km throughout.

Thus

$$\text{Total cost}, C_o = S + 2T_o + T_n + C_u + C_s,$$

where: S = set-up costs at base = $S_h \times$ w, given a set-up time (S_h hr) and an hourly labor rate (w).

T_o = travel cost between base and start of network = $[B_t \times \text{w}] + [B_d \times \text{v}]$, where B_t = travel time between base and start of network, B_d = distance (km) between base and start of network, and v = vehicle running costs per km.

T_n = travel costs around network = $[N_t \times \text{w}] + [N_d \times \text{v}]$, given N_t and N_d are the travelling time required and distance around the network, respectively.

C_u = total trap service costs for unsprung traps = $U_n \times U_t \times w$, where U_n is the number of unsprung traps and U_t is the time to check an unsprung trap.

C_s = total trap service costs for sprung traps = $S_n \times S_t \times w$, where S_n is the number of sprung traps and S_t is the time to check a sprung trap.

We next estimated operational costs incurred using a WSN, both with and without a 5-day service–rebaiting visit. With a WSN, a trapper needs only to visit those traps recorded as sprung, but the exact daily travel and labor costs depend on where those sprung traps are in the network. For simplicity, we assumed that visiting any subset of sprung traps within the network incurred 50% of the daily costs of travelling around the whole network. Savings were estimated as the difference between operational costs without a WSN and those under each WSN scenario.

Benefits Versus Costs

For any new technology to be implemented by a management agency the potential benefits, whether expressed in monetary or nonmonetary (e.g., biodiversity) metrics, will need to outweigh the establishment and maintenance costs. One method of doing this is to estimate a benefit:cost ratio for the project; this is the ratio of the total predicted benefits (*B*; in this case, operational savings) from the project, discounted at a rate, *r*, over a defined period, *t*, to the similarly discounted net project costs, *C*. In this context, "discounting" refers to the economic principle of applying a discount rate to a value. This is a compounding interest rate applied in reverse, from future to present, such that future costs and benefits can be expressed as net present value in today's currency values. This allows comparisons of current and future costs and benefits in a common metric and at a common point in time. Thus,

$$BCR = \frac{\sum_{t=1}^{t} \frac{B_t}{(1+r)^t}}{\sum_{t=1}^{t} \frac{C_t}{(1+r)t}}$$

A project with a benefit:cost ratio $\geq$1.0 is considered a potentially worthwhile economic investment. This method, or variants of it, have been used to evaluate the cost-effectiveness of a range of environmental projects or as a means of ranking competing projects over the past 2 decades (Cullen 2012, Newton et al. 2012, Pannell et al. 2013).

We based our network set-up costs for each size of WSN on a commercially available system wherein each trap in the network is fitted with a trigger that signals the trap being sprung. Up to 4 triggers can communicate with a single node (we assumed a conservative 3/node). All nodes then communicate wirelessly with a single base-station, which, in turn, passes on the information via a satellite link to the Internet. We obtained unit costs for trap triggers (NZ $40), nodes (NZ $550, including 2 rechargeable batteries), and solar-powered base-stations (NZ $2,430) from an Australasian manufacturer. We assumed an ongoing annual cost of 2.5% of those values for maintenance and support based on the assumption that our relatively simple system with rechargeable batteries would require less ongoing maintenance than would the complex environmental sensor-based system of Navarro et al. (2014), who estimated maintenance at 8% of total costs. Ongoing costs were discounted to net present costs using a discount rate of 5% over 10 years. This rate has been used by other studies of environmental projects (e.g., Pannell 2013, Markandya 2014) and lies within the range of recommended values for this type of study (Bell et al. 2011, Freeman and Groom 2013). Benefits over the same period were estimated as total annual savings discounted using the same rate.

RESULTS

We estimated the annual operational costs of checking all traps daily for 10 days each month to be $17,654 for a 150-trap network and $29,907 for a 300-trap network (New Zealand currency, 2015 benchmark). When a WSN was used to alert trappers to the presence of a sprung trap, approximately 50% of these costs could be saved when traps were visited only when sprung and rebaited every 5 days. If long-life bait lasting 10 days was used, up to 70% of operational costs could be saved (Table 1).

Cost savings were greater when more traps were included in the network; doubling the number of traps led to a 10% increase in savings using either 5-day rebaiting or long-life bait. Savings also increased when the rate at which traps were sprung declined. For example, for a 150-trap network using long-life bait, monthly operational cost savings increased from 58% at a rate of 2.40 sprung traps/100 trap-nights to 79% with a trap-spring rate of 0.76/100 trap-nights (Fig. 2). In our deterministic example, variation around this relationship was affected by the number and distribution of zero-capture days in a trapping period. For example, the same number of sprung traps over a 10-day period may result in an even daily spread of sprung traps requiring the trapper to leave base and travel around at least

Table 1. Summary of estimated operational costs from running 2 sizes of a network of live-traps and savings accrued from using a wireless sensor network (WSN) to indicate presence of a sprung trap. Discounted annual savings over a 10-year operational life were compared with discounted network establishment and maintenance costs to estimate a benefit–cost ratio for each scenario.

Scenario	Operational costs (NZ$)	Savings (NZ$)	Savings (%)	Establishment costs (NZ$)	Benefit-cost ratio
Daily checks (150 traps)	17,653			35,930 (150 traps)	
WSN 5-day rebaiting (150 traps)	8,652	9,001	51		1.57
WSN no rebaiting (150 traps)	6,405	11,249	64		1.96
Daily checks (300 traps)	29,907			69,430 (300 traps)	
WSN 5-day rebaiting (300 traps)	13,165	16,742	56		1.58
WSN no rebaiting (300 traps)	8,985	20,922	70		1.97

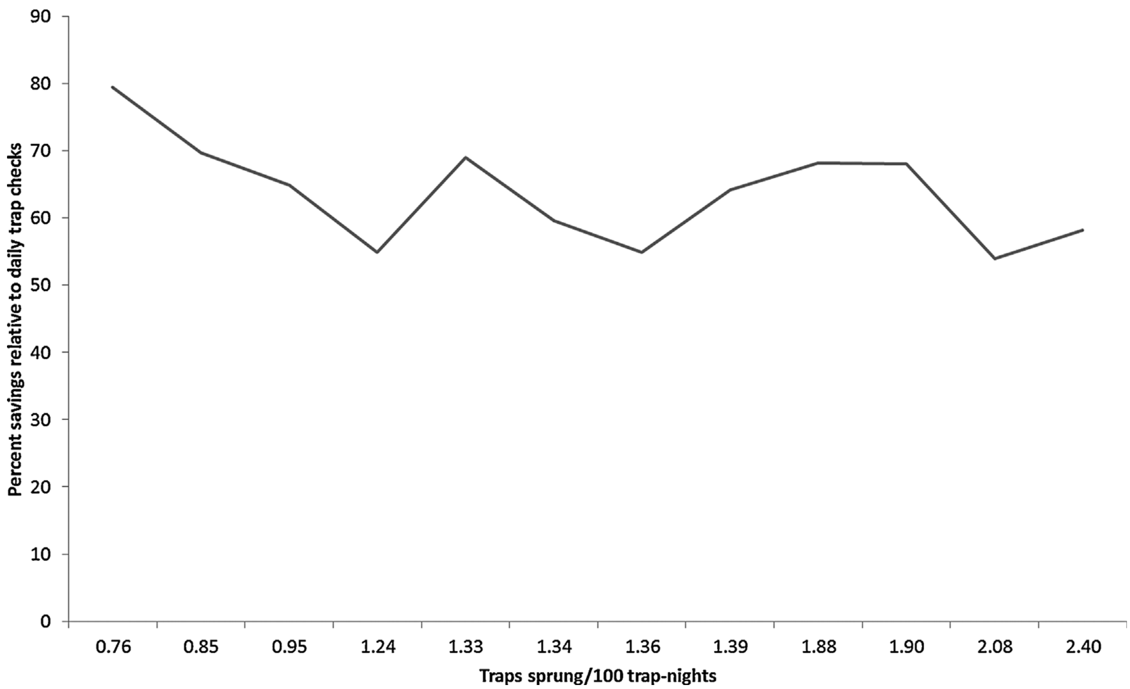

Figure 2. Effects of variability in the mean rate of sprung traps on monthly operational savings in monitoring and servicing costs of a live-trapping network of 150 traps from using a wireless sensor network. Operational savings are defined as the difference in costs between monitoring all traps daily for 10 days/month and only servicing those traps indicated as sprung via the network. Savings are generally greater at lower trap-spring rates, but within trapping periods, exact savings will vary because of the number of zero-capture days within the period.

part of the network every day. Alternatively, spring events may be distributed unevenly so that, on some days, no traps are sprung, but on others greater than "average" events occur. Under the former scenario, proportionally greater monthly cost savings will accrue because a trapper knows not to leave base and all transport costs are saved. In a more realistic stochastic environment, these effects are likely to even out over time, resulting in a smoother trend relationship. Use of a WSN was cost-effective (benefit:cost ratio >1) for all 4 modeled scenarios (Table 1). For both sizes of network, use of long-life baits resulted in greater cost-effectiveness, with the larger network slightly more cost-effective than the smaller.

DISCUSSION

Wireless sensor networks are already in use in environmental monitoring programs around the world (Martincic and Schwiebert 2005, Porter et al. 2005). Although, in most current examples of use, the network represents a largely passive monitoring system, wireless sensor networks can provide significant operational cost savings as part of an interactive system in which labor requirements are directed only where and when required. Live-trapping networks are an example of such an interactive system. Our simple economic model suggested that considerable operational cost savings can be achieved by the use of a wireless sensor network to identify sprung traps compared with the current practice of checking all traps every day. Clearly, potential savings from using a wireless sensor network in any particular trapping program should be assessed before committing to the use of the technology because the particular benefits depend on a complex interaction between the number of traps, extent of network, topography and vehicle access, trap spring rates and bait longevity, and cost of implementing a wireless sensor network.

In our modeled example, results suggested that use of wireless sensor networks could be justified economically. Clearly, many potential combinations of trapping networks and their applications could be modeled, and modeling of specific scenarios can provide useful information to guide investment in expensive new technology. Such modeling should reflect the network under test and the particular needs, both in terms of the study or survey data and operational requirements. For example, both land use (e.g., open farmland or dense bush) and topography may determine whether a trapper can reach the traps by vehicle or will need to travel on foot. This will alter the costs and savings associated with vehicle running costs and labor time. Our simple modeling approach could be readily extended to include more complex spatial modeling to investigate relative costs and benefits of a variety of network designs.

In our example, savings from using wireless sensor networks in trapping programs are likely to increase with both number of traps in the network and duration of trapping sessions. However, as trapping networks increase in size, savings from a trapper visiting only those traps identified by the wireless sensor network as sprung will depend on where those traps are in the network and relative costs of visiting only those sprung traps compared with having to travel around the entire network. Temporal limitations will depend on the study goals for the network. For example, a live-trapping program aimed at obtaining data for use in closed-population capture–mark–recapture models to estimate the local abundance of a species will only operate for the period over which the study population can be assumed to be closed (typically around 10 days) before analytical assumptions are violated (Otis et al. 1978). Perhaps the best case for using a wireless sensor network for monitoring trap status is where large-scale permanently operating trap infrastructures are required for ongoing monitoring or specific control of key threatened or pest species.

Other direct, measurable benefits from using wireless sensor networks to monitor trap networks include reductions in vehicle use leading to both economic and environmental benefits, and the ability to redeploy labor within an organization because of reduced time demands from visiting fewer traps daily. However, potential savings will only be realized if staff can be deployed usefully in other jobs when not checking traps.

Other potentially important benefits from using wireless sensor networks in trapping programs are linked to system data-gathering abilities. Perhaps the most useful, both in kill-trapping programs aimed at pest species and in gathering data on rare or cryptic species using live traps or trail cameras, is the potential for optimizing trapping network design to increase probabilities of trap encounter. Precise spatial and temporal data on trap success could be used to refine operational designs, including trap placement, trap density, and servicing frequency, thus increasing precision in spatial and temporal trap-placement design at greater resolution than that provided currently by Global Positioning System-based studies of animal movements (e.g., Jones and Norbury 2006, Shanahan et al. 2007, Recio et al. 2013) or regression-type approaches linking habitat variables to trapping rates (Cameron et al. 2005). Sensors in wireless sensor networks could also be used for monitoring other operational parameters such as presence of wildlife close to the trap—using infrared, or animal behavior around the trap—using cameras or motion sensors (Garcia-Sanchez et al. 2010). In capture–mark–recapture studies, wireless sensor networks could potentially be used to record sensor interactions with animals marked with, for example, radio frequency identification or passive integrated transponder tags (Fagerstone and Johns 1987, Morley 2002) to reduce both field costs and the need to trap and handle individual animals repeatedly. Furthermore, wireless sensor networks could be used to test the effectiveness of new traps, baits, or localized aspects of trapping network design.

Wireless sensor networks bring a number of more general benefits to the field of environmental monitoring and control. These include the ability to gather large volumes of long-term data for minimal field labor costs after initial set-up. This is partly due to the ability of the nodes to go to sleep when there is no activity, allowing battery power to last for years, or for sensor nodes to be powered by ambient energy harvesting (through micro solar, hydro, air movement, or vibration; Chou et al. 2011). Furthermore, the potential number of measurements greatly increases because of the long-term presence of the sensors, thus increasing the value of the results proportional to the required initial effort. Compared with unconnected sensors, wireless sensor networks can also transmit the sensor data quickly, making measurements available in near real-time. This enables automatic control of other systems or rapid responses to threats to biological assets. In addition, the current protocols for wireless sensor networks enable self-healing and self-organizing networks, which ensure that occasional node failures do not affect the rest of the network, making it a robust system. Compared with other sensor systems where all measurement data are stored at the sensors until somebody manually retrieves the data, wireless sensor networks have a much lower risk of losing data. In wireless sensor networks, data are retrieved from sensors immediately, and can be sent to data loggers or web servers in real-time, providing much better back-up facilities than possible when storing data at individual sensors in the field.

There are a number of factors that will constrain the magnitude of potential benefits of wireless sensor networks in trapping operations. Our simulations suggested that operational cost savings from their use would be greater if traps did not need rebaiting frequently. In New Zealand, the most commonly used bait for trapping introduced vertebrate predators is fresh or salted rabbit (*Oryctolagus cuniculus*) meat, which can become unattractive from a few days to a month after deployment depending on climate and environment. The development of attractive long-life bait (Spurr 1999) would greatly increase the cost-effectiveness of wireless sensor networks in trapping programs. Furthermore, traps need regular servicing to maintain effectiveness. Servicing requirements put an upper bound on the time a trap can be left unserviced. This upper bound is, however, much higher than that for bait longevity.

In small-mammal control programs, traps are often set in lines 50–200 m apart with up to hundreds of meters between lines (Department of Conservation, unpublished data). Wireless networking protocols commonly used by wireless sensor networks work at the range of $\leq$150 m. Self-healing properties of networks require nodes to be distributed such that each node can communicate with at least 2 or 3 other nodes. This will not work in lines of traps where, in effect, the nodes are in a chain rather than a mesh. If one node fails, all the other nodes distal to that point will cease to be accessible from the base station. This constraint can be minimized by having base stations positioned at both ends of a line, or by replacing nodes each time they fail. This is unlikely to be a constraint for grid- or mesh-based trapping programs (Porter et al. 2005).

There may also be constraints on use in live-catch traps because of animal welfare legal and regulatory requirements, depending on whether checking a trap remotely (using an electronic sensor showing whether the trap has been sprung) can be considered "inspecting" a trap as is required by some authorities (Johansson et al. 2011). Trials may need to be conducted, technology certified, and processes and even legislation amended before wireless sensor networks could be used in this context. Users must also be aware of the animal welfare impacts of equipment failure leading to excessive holding periods within traps not indicated as sprung, although the self-healing and automated error reporting abilities of networks should mitigate this risk to a large extent.

As with any new technology, system component costs may initially be high. In our example, despite relatively expensive establishment costs of up to almost NZ $69,500 for the larger network, the investment was cost-effective in terms of operational savings. With increased uptake of the technology, it would be expected that equipment costs would show a relative decrease, making the technology an even more attractive investment. We emphasize, though, that managers should examine each potential technology application on its own merits and assess relative costs and benefits appropriately as part of any funding decision.

Wireless sensor networks have potential to decrease operational costs of terrestrial wildlife trapping and monitoring programs significantly, particularly those involving labor-intensive live-trapping. Furthermore, wireless sensor networks have the ability to collect, transmit and store vast volumes of environmental data that may be used in research or to refine wildlife management or monitoring. Their immediate use on a widespread scale is likely to be constrained by uncertainties around establishment costs relative to longer term savings and also by requirements for field staff to service or check traps because of legislation or bait attractiveness.

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LITERATURE CITED

Bell, B., C. Cudby, and M. Yap. 2011. Biodiversity valuation manual: a technical manual for MAF Biosecurity New Zealand. Revised. Nimmo-Bell, Wellington, New Zealand.

Benevides, F. L. Jr., H. Hansen, and S. C. Hess. 2008. Design and evaluation of a simple signaling device for live traps. Journal of Wildlife Management 72:1434–1436.

Cameron, B. G., Y. van Heezik, R. F. Maloney, P. J. Seddon, and J. A. Harraway. 2005. Improving predator capture rates: analysis of river margin trap site data in the Waitaki Basin, New Zealand. New Zealand Journal of Ecology 29:117–128.

Chou, S. K., W. M. Yang, K. J. Chua, J. Li, and K. L. Zhang. 2011. Development of micro power generators—a review. Applied Energy 88:1–16.

Cullen, R. 2012. Biodiversity protection prioritisation: a 25-year review. Wildlife Research 40:108–116. doi: 10.1071/ WR12065

Darrow, P. A., and J. A. Shivik. 2008. A pilot evaluation of trap monitors by the USDA Wildlife Services Operational Program. Proceedings of Vertebrate Pest Conference 23:213–217.

Fagerstone, K. A., and B. E. Johns. 1987. Transponders as permanent identification markers for domestic ferrets, black-footed ferrets, and other wildlife. Journal of Wildlife Management 51:294–297.

Freeman, M. C., and B. Groom. 2013. Biodiversity valuation and the discount rate problem. Accounting, Auditing and Accountability Journal 26:715–745.

Garcia-Sanchez, A.-J., F. Garcia-Sanchez, F. Losilla, P. Kulakowski, J. Garcia-Haro, A. Rodríguez, J.-V. López-Bao, and F. Palomares. 2010. Wireless sensor network deployment for monitoring wildlife passages. Sensors 10:7236–7263.

Gebhardt, K., S. A. Shwiff, B. R. Leland, D. R. Hatchett, and M. J. Bodenchuk. 2009. Methodology to estimate cost savings associated with the use of trap monitor systems by Wildlife Services. J. R. Boulanger, editor. Proceedings of the 13th wildlife damage management conference. http://digitalcommons.unl. edu/ icwdm_wdmconfproc/112/. Accessed 22 Aug 2014.

Goodrich, J. M., L. L. Kerley, B. O. Schleyer, D. G. Miquelle, K. S. Quigley, Y. N. Smirnov, I. G. Nikolaev, H. B. Quigley, and M. G. Hornocker. 2001. Capture and chemical anesthesia of Amur (Siberian) tigers. Wildlife Society Bulletin 29:533–542.

Hayes, R. W. 1982. A telemetry device to monitor big game traps. Journal of Wildlife Management 46:551–553.

Johansson, A. T., Ö. Johansson, and T. McCarthy. 2011. An automatic VHF transmitter monitoring system for wildlife research. Wildlife Society Bulletin 35:489–493.

Jones, C., and G. Norbury. 2006. Habitat use as a predictor of nest raiding by individual hedgehogs *Erinaceus europaeus* in New Zealand. Pacific Conservation Biology 12:180–188.

Juang, P., H. Oki, Y. Wang, M. Martonosi, L. S. Peh, and D. Rubenstein. 2002. Energy-efficient computing for wildlife tracking: design tradeoffs and early experiences with ZebraNet. ACM (Association for Computing Machinery) SIGPLAN Notices 37(10):96–107.

King, C. M., editor. 2005. Handbook of New Zealand mammals. Second edition. Oxford University Press, Melbourne, Victoria, Australia.

Larkin, R. P., T. R. Van Deelen, R. M. Sabick, T. E. Gosselink, and R. E. Warner. 2003. Electronic signaling for prompt removal of an animal from a trap. Wildlife Society Bulletin 31:392–398.

Mainwaring, A., D. Culler, J. Polastre, R. Szewczyk, and J. Anderson. 2002. Wireless sensor networks for habitat monitoring. Pages 88-97 *in* WSNA '02 Proceedings of the 1st ACM international workshop on wireless sensor networks and applications. Association for Computing Machinery, New York, New York, USA.

Markandya, A. 2014. Benefits and costs of the biodiversity targets for the post-2015 development agenda. Copenhagen Consensus Center Biodiversity Assessment Paper, Copenhagen, Denmark. http://www.copenhagenconsensus.com/sites/default/files/biodiversity_assessment_-_markandya.pdf. Accessed 16 Dec 2014.

Marks, C. A. 1996. A radiotelemetry system for monitoring the treadle snare in programmes for control of wild canids. Wildlife Research 23:381–386. http://dx.doi.org/10.1071/WR9960381.

Martincic, F., and L. Schwiebert. 2005. Introduction to wireless sensor networking. Pages 1–41 *in* I. Stojmenović, editor. Handbook of sensor networks: algorithms and architectures. John Wiley, Hoboken, New Jersey, USA.

Morley, C. G. 2002. Evaluating the performance of PIT tags and ear tags in a capture-recapture experiment. New Zealand Journal of Zoology 29: 143–148.

Navarro, M., T. W. Davis, G. Villalba, Y. Li, X. Zhong, N. Erratt, X. Liang, and Y. Liang. 2014. Towards long-term multi-hop WSN deployments for environmental monitoring: an experimental network evaluation. Journal of Sensor and Acuator Networks 4:297–330.

Newton, A. C., K. Hodder, E. Cantarello, L. Perrella, J.C. Birch, J. Robins, S. Douglas, C. Moody, and J. Cordingley. 2012. Cost-benefit analysis of ecological networks assessed through spatial analysis of ecosystem services. Journal of Applied Ecology 49:571–580.

Nolan, J. W., R. H. Russell, and F. Anderka. 1984. Transmitters for monitoring Aldrich snares set for grizzly bears. Journal of Wildlife Management 48:942–945.

Ó Néill, L., A. de Jongh, J. Ozoliņš, T. de Jong, and J. Rochford. 2007. Minimizing leg-hold trapping trauma for otters with mobile phone technology. Journal of Wildlife Management 71:2776–2780.

Otis, D. L., K. P. Burnham, G. C. White, and D. R. Anderson. 1978. Statistical inference from capture data on closed animal populations. Wildlife Monographs 62.

Pannell, D. J. 2013. Ranking environmental projects. University of Western Australia, School of Agricultural and Resource Economics Working Paper 1312, Crawley, Australia.

Pannell, D. J., A. M. Roberts, G. Park, and J. Alexander. 2013. Designing a practical and rigorous framework for comprehensive evaluation and prioritization of environmental projects. Wildlife Research 40:126–133.

Porter, J., P. Arzberger, H.-W. Braun, P. Bryant, S. Gage, T. Hansen, P. Hanson, C.-C. Lin, F.-P. Lin, T. Kratz, W. Michener, S. Shapiro, and T. Williams. 2005. Wireless sensor networks for ecology. BioScience 55: 561–572.

Porter, J. H., P. C. Hanson, and C.-C. Lin. 2012. Staying afloat in the sensor data deluge. Trends in Ecology & Evolution 27:121–129.

Recio, M. R., R. Mathieu, M. C. Latham, A. D. M. Latham, and P. J. Seddon. 2013. Quantifying fine-scale resource selection by introduced European hedgehogs (*Erinaceus europaeus*) in ecologically sensitive areas. Biological Invasions 15:1807–1818.

Shanahan, D. F., R. Mathieu, and P. J. Seddon. 2007. Fine-scale movement of the European hedgehog: an application of spool-and-thread tracking. New Zealand Journal of Ecology 31:160–168.

Spurr, E. B. 1999. Developing a long-life toxic bait and lures for mustelids. Science for Conservation 127:1–24.

Szewczyk, R., A. Mainwaring, J. Polastre, J. Anderson, and D. Culler. 2004*a*. An analysis of a large scale habitat monitoring application. Pages 214-226 *in* Proceedings of the 2nd international conference on embedded networked sensor systems. Association for Computing Machinery, New York, New York, USA.

Szewczyk, R., E. Osterweil, J. Polastre, M. Hamilton, A. Mainwaring, and D. Estrin. 2004*b*. Habitat monitoring with sensor networks. Communications of the ACM 47:34–40.

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