Remote Monitoring in the COVID-19 Context

Remote Monitoring: Considerations for Practitioners based on Recent Literature

By Jacob Patterson-Stein and Christine Canavan

The COVID-19 pandemic has forced a reexamination of how data are collected as part of Third-Party Monitoring (TPM). At a time when most mobile phones have over a dozen sensors built into their hardware, what may feel like drastic changes in data collection now are, in the long view, largely part of a move toward remote monitoring as the primary source of development data. From publicly available satellite data to monitor cultural heritage sites to using mobile phone meta-data to understand travel patterns, a growing literature explores the trade-offs in using remote data to track, monitor, and assess development activities.

As a leader in TPM, Management Systems International (MSI) has summarized various approaches for using remote data for TPM. This summary highlights the tools that should be considered by TPM practitioners, followed by a summary of the pros and cons, and relevant examples from recent literature. The final section depicts a summary decision tree for considering what approach may be most relevant. Remote monitoring, like any data collection effort, needs to be contextually relevant, culturally sensitive, and technically rigorous. The decision tree and overall review of tools is a starting point for practitioners to consider what approach or combination of approaches will work best for their TPM activities.

Approaches to Remote TPM

There are two general categories of remote monitoring: remote data collection and remote sensing. Remote data collection is built on many of the same assumptions and methods as in-person qualitative or structured survey work, but there is no direct engagement between researchers or enumerators and respondents. In contrast, remote sensing broadly observes behaviors or activities using satellites, in-situ measurement devices, or drones. A key distinction between the two approaches is that remote sensing relies largely on observation, whereas remote data collection is self-reported.

This paper was prepared by MSI staff to contribute to the discussion and understanding of the important development challenges facing policymakers and practitioners.
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The reviewed literature identifies five main approaches for remote data collection. Each approach assumes mobile phone coverage, with some requiring internet or mobile data. Basic feature phones and, increasingly, smart phones are accessible in almost every country, including low- and middle-income countries (Taylor and Silver 2019). This paper reviews the following approaches:

**INTERACTIVE VOICE RESPONSE (IVR):** Delivers questions via audio recordings while respondents reply via the keypad or through simple audio responses. This approach can include outgoing calls or a hotline that collects incoming responses from participants who dial-in. The approach requires a roster of phone numbers.

**COMPUTER ASSISTED TELEPHONE INTERVIEWS (CATI):** A remote, interviewer-assisted approach that involves administering a structured survey via telephone. This approach is most similar to implementing a survey face-to-face as it involves talking to respondents. The approach requires a roster of phone numbers.

**SHORT MESSAGE SERVICE (SMS):** A text-based survey sent remotely to mobile phones with respondents answering questions via the touchpad. There is no human engagement. The approach requires a roster of phone numbers.

**MOBILE INSTANT MESSAGE (MIM) AND SOCIAL MEDIA GROUPS:** The use of mobile text, photo, and video applications, and social media to collect observations and open text responses to TPM-facilitated questions and moderated discussions. Platforms such as WhatsApp can be used to facilitate group discussions or hold daily check-ins with a group of participants. Moderated social media groups can serve a similar role, with facilitated questions posed to the group.

**ONLINE SURVEY:** Respondents directly engage with a structured survey instrument via an internet connected computer or mobile device without interviewer assistance. No human engagement is needed. Users can either be targeted through email or SMS, or the survey link can be promoted through social or other media.

Remote Tools, Local Context

As with any data collection effort, local context should drive the approach. If a roster of phone numbers is not available, random digit dialing may be an option to develop such a roster. This approach was used in Afghanistan to develop a sample of potential respondents for an IVR survey (Leo et al, 2015). In other cases, agreements with local mobile carriers may provide a sample of respondents for a remote survey. However, as Leo et al. (2015) note, the number of national carriers, costs to coordinate with carriers, and variation in carrier subscription can make this approach logistically difficult and costly.

In many cases, a combination of methods may yield the best results (Greenleaf et al. 2017). For example, in South Sudan, face-to-face interviews were combined with mobile phone follow-up interviews to capture recurrent household data (Demombynes, Gubbins, and Romeo 2013). Sending SMS reminders ahead of CATI calls can improve response rates (Kasy and Sautmann 2019, Morse et al. 2016).
Sampling and Remote Data Collection
Sampling poses challenges for remote monitoring. Because sampling frames for remote data collection exclude individuals without access to, or willingness to use, appropriate technologies, they are not representative of the broader population. Unobservable differences between respondents willing to answer the phone or respond to a text and those who cannot or prefer not to respond to a remotely applied survey likely exist and can skew analysis. Researchers need to consider potential sample biases when selecting a remote data collection method. Hight et al. (2017) note that mobile phone access, mobile data usage, and text message usage vary by gender and age, with women less likely to have mobile access and to use mobile data. World Bank research also suggests that younger populations are more likely to respond to SMS surveys (see Ballivian et al. 2015 and Du et al. 2013). The literature on MIM for TPM is limited, but the same sampling challenges are likely to apply. In contexts where smartphone use is concentrated among youths or people with more education, MIM and social media groups may present serious TPM design and analytical concerns.

Mobile Data Requirements May be a Burden
Mobile data requirements must also be considered. While SMS surveys can generally be designed such that the TPM implementer bears the messaging costs, online surveys and mobile instant messaging and social media groups often require access to mobile data. Mobile instant messaging and social media groups give TPM implementers the ability to collect observations from people on the ground or allow for focus group-style discussions, but can be difficult to manage (Raftree 2017, Kaufman and Peil 2019). Platforms such as WhatsApp do not always protect participant identities, with some practitioners developing their own chat platforms to engage with respondents anonymously (Richards 2019).

These issues are summarized in Table 1 below. While not an exhaustive review of the pros and cons of each remote data collection approach, the table highlights issues raised in the literature and provides a starting point for weighing which mode or modes to use.
<table>
<thead>
<tr>
<th>APPROACH</th>
<th>STRENGTHS</th>
<th>LIMITATIONS</th>
<th>IT REQUIREMENTS</th>
<th>GENERAL COSTS (USD CURRENT)</th>
<th>EXAMPLE</th>
</tr>
</thead>
</table>
| **IVR**  | • No variation in application of questionnaire  
• Low cost  
• No literacy constraint  
• Easy to contact large sample  
• Rapid deployment, rapid responses  
• Anonymous  
• Can be run at any time of the day  
• Respondents can initiate contact  
| • Low response rates (<20%)  
• High attrition  
• No ability to capture respondent feedback or open-ended questions  
• Limited language options  
• Responses tend to differ compared to in-person interviews  
• Binary and five-point Likert questions work best  
| • Local phone plan  
• IVR survey software platform  
• Local phone  
| • $7-9 per completed questionnaire  
• IVR platform license fee <$500  
| • Somalia to collect household food security data (Dette et al. 2016).  
• The World Bank used IVR to survey re-settled refugees in Afghanistan (Krishnan et al. 2018).  |
| **CATI** | • Low cost compared to face-to-face surveys  
• No literacy constraint  
• Potential for adapting to multiple languages if the interviewer team has capacity.  
• Responses are generally similar to in-person interviews  
• Easy to engage respondents and clarify questions  
• Binary, and five-point Likert, and brief open text questions permissible  
| • Low response rates (<50%)  
• High attrition  
• Inter-rater reliability concerns  
• Requires a trained team of interviewers  
| • Phones  
• Headsets for making calls  
• Online or tablet survey software  
| • $5-20 per completed questionnaire  
| • The World Bank used CATI for real-time monitoring in Liberia during the Ebola outbreak (Etang and Himelin 2020).  
• Applied in Lebanon to capture population data (Mahfoud 2014).  |
| **SMS**  | • No variation in application of questionnaire  
• Low cost  
• Easy to contact large sample  
• Rapid deployment, rapid responses  
• Anonymous  
• Can be run at any time of the day  
• Can easily provide mobile credit incentive  
| • Literacy constraint  
• Low response rate (<20%)  
• Very high attrition due to change in numbers between survey rounds for longitudinal surveys  
• No ability to capture respondent feedback or open-ended questions.  
• Responses tend to differ compared to in-person interviews  
• No more than 10 questions recommended  
• Binary and five-point Likert questions work best  
• Potential age and gender bias  
| • Local phone plan  
• SMS survey software  
• Local phone  
| • $1-6 per respondent for a 10-question survey  
• SMS platform license fee <$200  
| • UNICEF used SMS surveys for real time monitoring in multiple conflict and post-conflict countries to track health, education, and household income data (Wexler and Yang 2018).  
• SMS messages were used in Liberia to track and monitor Ebola (Feng et al. 2018).  |
<table>
<thead>
<tr>
<th><strong>MIM</strong></th>
<th><strong>ONLINE SURVEY</strong></th>
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</table>
| • Low cost  
• Allows for qualitative data collection such as focus group-style discussions  
• Can be run at any time of the day  
• User-driven, which can improve engagement with questions  
• Literacy constraint  
• Difficult to manage if groups become large  
• Anonymity may be difficult to maintain  
• May require well-targeted, relevant content to elicit responses  
• Potential gender and youth bias  
• Platforms may be banned in TPM countries | • No variation in application of questionnaire  
• Low cost  
• Easy to contact a large sample via email, social media, or SMS to share survey link  
• Multiple question types  
• Easy to track respondents via meta data  
• Possible to provide online incentive  
• Some evidence that medium (computer vs. mobile phone) affects responses  
• Literacy constraint  
• Low response rate (<20%)  
• Requires internet connectivity  
• Potential age and gender bias  
| • Phone or computer with relevant applications loaded  
• Free, with some pay schemes for upgraded business features  
| • Basic survey platforms are free, but proprietary license costs vary.  

• WhatsApp was used in Syria to monitor attacks on health services in real time (Elamein 2017)  
• UNDP is using a WhatsApp messaging project to share news about COVID-19 (UNDP 2020)  
• Used to survey donor staff in Afghanistan, Somalia, South Sudan, and Turkey/Jordan (Steets et al. 2016)
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Remote Sensing and Other Observation Approaches
Remote sensing is ideal in situations where prior in-person work entailed tracking and validating the existence of development activities, ensuring functionality, or observing changes over time that do not involve perceptions. In rural Kenya, sensors on water borehole pumps were installed to broadcast pump functionality data, which allowed for real-time tracking of breakdowns in drought-prone areas (Turman-Bryant et al. 2019). A similar study in Nairobi combined real-time sensor tracking with predictive modelling to improve targeting of toilet repairs which replaced the use of in-person monitors to regularly assess toilets (Turman-Bryant, et al 2019). For many remote sensing approaches, data are combined with classification algorithms to process and interpret findings. Machine learning may be critical in some cases to make the large amount of data generated comprehensible (Quinn et al. 2018). As shown in Table 2, remote sensing for TPM solves some access problems, but comes with limitations that need to be carefully assessed, as well.

The remote sensing approaches identified in the literature are summarized below:

**IN-SITU SENSORS:** Sensors are placed at a site to track an activity, such as water flow, particulate concentration, seismic activity, number of entries/exits, or acoustics. Size, power source, and memory capacity vary. Some in-situ sensors can broadcast data over satellite or cellular networks, while others require periodic, on-site data downloads.

**EARTH OBSERVATION/SATELLITE DATA:** Collected by national and international bodies, data are recorded at a near-constant rate from the earth’s surface. Publicly available data on nighttime light, precipitation, road construction, forest and vegetation cover, and land use are easily accessible.

**UAV:** Generally, user-controlled small aerial vehicles that can capture images, apply light detection and ranging (LiDAR), and assist in capturing geo-spatial information from several hundred to several thousand feet high.

**META-DATA:** Call detail records (CDRs) can provide basic information on all communication flows over a network, such where and when calls and text messages originated.

All the approaches above avoid active engagement with the TPM subject. This may be valuable in cases where repeated assessments can alter behavior or present a danger to the person or place being monitored. Each approach monitors actual rather than reported activity. For example, in India, in-situ sensors measuring latrine use recorded much lower use than when a human observers were present (Clasen et al. 2012).

**Sampling is Still an Issue for Remote Sensing**
The challenge of sample selection is applicable to remote sensing and other remote observation approaches. In-situ sensors must be installed or placed at the relevant monitoring site. This may pose a risk to the installation team, but site selection may also over- or under-represent certain populations, behaviors, or phenomena. Satellite data are less prone to such limitations, but are less able to observe relevant indoor behavior. The challenges of cloud cover or, in some cases, temporal coverage can also affect sampling and availability for satellite data.
Ethical Considerations and Remote Sensing

The guidelines used in face-to-face data collection and human-based observation to protect human subjects (informed consent, do no harm, protection of identifiable information) are also applicable to remote data collection. However, remote sensing presents an ethical challenge in that respondents or participants often cannot give consent. Although many countries do not regulate the use of remote sensing, practitioners must ensure the privacy and risk of people living near a TPM site (Stöcker et al. 2012).

### Table 2: Remote Sensing Approaches

<table>
<thead>
<tr>
<th>APPROACH</th>
<th>STRENGTHS</th>
<th>LIMITATIONS</th>
<th>IT REQUIREMENTS</th>
<th>GENERAL COSTS (USD CURRENT)</th>
<th>EXAMPLE</th>
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</thead>
<tbody>
<tr>
<td><strong>IN-SITU SENSORS</strong></td>
<td>• Continuously capture localized behavior (e.g., cookstove use)</td>
<td>• Sensors have to be installed</td>
<td>• Local phone plan or satellite connection for transmitting sensors</td>
<td>Prices vary from &lt;$50 to $600</td>
<td>• Used in Syria to capture acoustic sounds correlated with Russian bombing to develop an early warning system (Hala 2018)</td>
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<td></td>
<td>• Some sensors broadcast data, which removes the need to revisit sites</td>
<td>• Theft</td>
<td>• Software for conversion of sensor data to readable format</td>
<td></td>
<td>• Deployed in Indonesia to monitor handwashing practices (Thomas 2013)</td>
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<td></td>
<td>• No enumerator bias in monitoring of recurring events or usage</td>
<td>• Battery life</td>
<td></td>
<td></td>
<td>• Used in Indonesia to monitor conservation efforts (Koh and Wich 2012)</td>
</tr>
<tr>
<td></td>
<td>• Possible to obtain consent from participants prior to sensor installation</td>
<td>• Memory limits for non-transmitting sensors</td>
<td></td>
<td></td>
<td>• Multiple use cases for agricultural monitoring (CRS 2019)</td>
</tr>
<tr>
<td><strong>SATELLITE</strong></td>
<td>• Regular time series that is comparable across periods and locations</td>
<td>• Data stored in formats that require special software and/or skills to access and interpret</td>
<td>• High bandwidth internet connection</td>
<td>Generally low, some datasets require license access</td>
<td>• USAID used satellite data to evaluate road construction in the West Bank (BenYishay 2019)</td>
</tr>
<tr>
<td></td>
<td>• Global coverage</td>
<td>• Small changes on the ground are not always observable</td>
<td>• Free, open source software</td>
<td></td>
<td>• Satellite data were used to track the scale of modern slavery in the “Brick Belt” countries across South Asia (Boyd et al. 2018)</td>
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<tr>
<td></td>
<td>• Many free sources</td>
<td>• Some sources may require agreements or licenses</td>
<td></td>
<td></td>
<td>• Researchers used satellite data to map, count, and categorize IDP settlements around the world (Quinn et al. 2018)</td>
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<tr>
<td></td>
<td>• Ability to make observations in conflict and remote locations</td>
<td>• No consent</td>
<td></td>
<td></td>
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</tr>
<tr>
<td></td>
<td>• Data are easy to map and visualize</td>
<td></td>
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<tr>
<td><strong>UAV</strong></td>
<td>• Ability to observe small scale activities that are unobservable by satellite</td>
<td>• Image data may require classification algorithms to use at scale</td>
<td>• UAV</td>
<td>$500-$25,000 for a UAV</td>
<td>• Used in Indonesia to monitor conservation efforts (Koh and Wich 2012)</td>
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<td></td>
<td>• High-resolution, 3D images can be captured</td>
<td>• Ethical concerns about privacy given high resolution imagery</td>
<td>• Open source statistical software for image classification</td>
<td></td>
<td>• Multiple use cases for agricultural monitoring (CRS 2019)</td>
</tr>
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<td></td>
<td>• Provides researcher access to otherwise inaccessible observation points</td>
<td>• History of targeted UAV strikes in some contexts may add sensitivity to deploying drones for TPM</td>
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<td>APPROACH</td>
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<tr>
<td>META DATA</td>
<td>• Large scale observation possible • Ability to capture connections between people within network • Provides approximate location information</td>
<td>• Serious privacy concerns given that no consent is provided and personal information is shared • No ability to capture information beyond a limited number of meta-fields • Requires cooperation and coordination with local mobile service providers • Real time monitoring may not be feasible</td>
<td>Monitoring software used in some cases</td>
<td>• Unknown</td>
<td>• Used in Rwanda to predict poverty and wealth (Blumenstock et al. 2015). • In Boston and Rio de Janeiro, call detail records were used to track travel over time (Colak 2014)</td>
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</tbody>
</table>

**Decision Tree**

The following tree provides a starting point for navigating the various approaches presented in this paper. For TPM activities that are transferring existing face-to-face data collection to a remote approach, there may be additional logistical considerations. The time to train, deploy, and scale each of these approaches will vary by country, what is being monitored, and the TPM team itself.
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