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EDITORIAL

Digital methods in epidemiology can transform disease control

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Modern society has been transformed by the digital revolution through cellular phones for communication, remote sensing of weather and other terrestrial data, cheap and plentiful digital computation and data storage, genomic sequencing and analysis, GPS for geolocation and navigation, and many other marvels. These advances have been concurrent with major changes in the burden, dynamics and distributions of diseases. The burden of disease remains intolerably high in much of the world,[1] and current challenges facing epidemiology include reducing the prevalence of both communicable and non-communicable diseases,[1] completing the Global Polio Eradication Initiative,[2] developing strategies to control and eliminate malaria,[2,3] and responding to outbreaks of emerging infectious diseases such as the recent Ebola epidemic.[4] In this special issue of *International Health*, the authors illustrate both the ways in which modern digital methods are already being applied to these current challenges in epidemiology and also the opportunities for even greater impact.

Remote sensing is already being applied to develop improved microplans for polio eradication efforts in Nigeria and these improved maps combined with GPS-enabled vaccinator tracking have helped the campaign achieve even higher coverage and performance.[2] Remote sensing of vegetation indices is explored for its ability to improve the linking of poverty, environment and health outcomes, thereby facilitating improved mapping of need and targeting of pro-poor interventions.[5] Multiple modern methods for mapping population movement are demonstrated and compared in the paper by Bharti et al.,[6] including remote sensing of nighttime lights and analysis of cell phone call data records. This capability for mapping population movements is especially critical during times of crisis, such as the Ebola outbreak,[7] and it is also useful in planning malaria elimination.[8]

Modern computational power and digital storage have facilitated some substantial advances, including recent successes in reverse vaccinology through the combination of next-generation sequencing with machine learning approaches.[9] Digital analysis of genomic data is transforming the fight against malaria and genomics are providing unprecedented tools for tracking and responding to challenges such as artemisinin resistance.[10] Modern computing facilitates analysis of the modes of spatiotemporal disease patterns through new algorithms, which can produce insights that inform disease control planning.[11] Genomic data can also inform understanding of spatiotemporal patterns of disease through new advances in phylogeography algorithms.[12] These new phylogeography algorithms are applied to the Ebola outbreak, influenza transmission and polio spread in northern Nigeria, and show how pathogens have dispersed geographically, findings that can be usefully combined with the mapping of human movements.

Advances in computing have allowed mathematical models of appropriate complexity to be applied to open questions in epidemiology and disease control. Mathematical models can be constructed to investigate different strategies for the control and elimination of malaria using varied combinations of vector control approaches.[3] A range of mathematical models are used to re-examine assumptions about the relative importance of targeting adult and larval stages of the mosquito life cycle, with varying degrees of complexity and with an understanding of spatial heterogeneity. Another modelling study[13] captures many of the key effects of health system structure on TB control in India and examines their implications for intervention strategies. This study also illustrates both the power of mathematical models built with modern day computational tools to prioritise data collection based on their value in reducing uncertainty in strategy formulation and also the importance of linking modelling to existing field efforts. Finally, the potential impact of targeted interventions in the generalized HIV epidemic in South Africa is explored through modeling.[14] Modelling enables the careful testing of assumptions about disease dynamics against data, showing the potential impact or lack of impact of proposed strategies. In the present case, the epidemic is found to have become too generalised for a focus on migrants in the mining industry to affect the national disease patterns disproportionately, although this may not have been the case earlier in the epidemic. While the results do not address the overall role of migration in the current epidemic, which is larger than just migration in the mining sector, the results demonstrate how a carefully constructed mathematical model can gain leverage on appropriately scoped policy questions.

Novel digital tools and data sources are driving demand for improved algorithms in interpreting remotely sensed data,[5,6] phylogeography,[12] genomics,[10] mathematical modelling[3,13,14] and dynamic mode decomposition.[11] The impact of these new algorithms and approaches will be maximised by collaborations among their developers and those in policy and field operations to ensure that new approaches are addressing questions that are most relevant. As the value of these modern digital methods continues to be demonstrated in real-world epidemiological applications, the rate of advance and scope of impact will only increase.

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