

Rodrigo, M.; Ajala, I.; Irhanida, A. K.

Article

A tourism area life cycle model with an index-dependent growth rate for modelling the poststagnation stage

Annals of Tourism Research Empirical Insights

Provided in Cooperation with:

Elsevier

Suggested Citation: Rodrigo, M.; Ajala, I.; Irhanida, A. K. (2025) : A tourism area life cycle model with an index-dependent growth rate for modelling the poststagnation stage, Annals of Tourism Research Empirical Insights, ISSN 2666-9579, Elsevier, Amsterdam, Vol. 6, Iss. 1, pp. 1-16, <https://doi.org/10.1016/j.annale.2025.100177>

This Version is available at:

<https://hdl.handle.net/10419/337835>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.



<https://creativecommons.org/licenses/by-nc-nd/4.0/>



A tourism area life cycle model with an index-dependent growth rate for modelling the poststagnation stage

M. Rodrigo^{a,*}, I. Ajala^b, A.K. Irhanida^c

^a School of Mathematics and Applied Statistics, University of Wollongong, Wollongong, New South Wales 2522, Australia

^b School of Humanities, Social Sciences and Health, University of Wollongong in Dubai, Knowledge Park, P.O. Box 20183, Dubai, United Arab Emirates

^c School of Hospitality, Tourism and Culinary Arts, UOW Malaysia KDU Penang University College, 10400 George Town, Penang, Malaysia

ARTICLE INFO

Handling Editor: Dr. Lorenzo Masiero

Keywords:

Tourism area life cycle

Poststagnation stage

Index-dependent growth rate

Periodic solutions

ABSTRACT

The resilience of the tourism industry is increasingly reliant on robust health infrastructure and effective disease detection systems, particularly in the face of ongoing global health challenges. This study introduces a modified tourism area life cycle model to explore the interplay between health preparedness and tourism dynamics. By linking growth rates to quantifiable indicators from the WHO International Health Regulations core capacity index, which evaluates adherence to global health standards, the model effectively illustrates tourist population behaviours alongside health capacity. It highlights trends of decline or rejuvenation during the poststagnation phase and provides predictive insights relevant to five representative countries.

1. Introduction

Butler's tourism area life cycle (TALC) model is a widely recognised framework for understanding the evolution of tourism destinations (Butler, 2006a, 2006b). It proposes an S-shaped growth life cycle with identifiable stages: exploration, involvement, development, consolidation and stagnation. The poststagnation phase can result in either decline or rejuvenation. The model's enduring influence stems from its descriptive capabilities, analytical strength, adaptability, policy planning relevance and its consideration of economic and territorial factors in tourism (Garay & Canoves, 2011; Jones, 2012; Knowles & Curtis, 1999; Petrevska & Collins-Kreiner, 2017; Polyzos et al., 2013).

The first five stages of a tourism destination's life cycle can be modelled using the logistic equation, with tourist arrivals over time as the state variable (Kraja & Beshiri, 2019; Lundtorp & Wanhill, 2001). The equation's solution reveals the characteristic S-shape seen in the early life cycle stages, attributed to a constant positive growth rate. This indicates that tourist numbers will rise until reaching the destination's carrying capacity.

Butler (2022) examined the COVID-19 pandemic's potential effects on tourism development, suggesting it may permanently alter travel habits and arguing that destinations in advanced development stages would be most impacted, with some questioning their viability. The present article explores an overlooked connection arising from these

findings: the relationship between tourism and public health preparedness.

This paper introduces a modified TALC model that features a growth rate influenced by quantifiable factors. Although other types of indices can be considered, we focus on the International Health Regulations (IHR) core capacity index, which gauges compliance with WHO IHR standards, providing extensive data coverage across numerous countries over a prolonged period. The proposal to modify the TALC model by incorporating health preparedness is both timely and critical, especially following the disruptions caused by the COVID-19 pandemic. The traditional TALC model fails to account for the impact of external shocks, such as health crises, on tourism dynamics. The pandemic has revealed significant vulnerabilities in the tourism sector, demonstrating that public health factors should be integral to any comprehensive tourism model.

A modified TALC model is essential for several reasons. Firstly, health preparedness emerges as a crucial determinant influencing tourism confidence. By including a health preparedness index, the model can illustrate how variations in public health readiness affect tourist inflows and destination viability. Additionally, rather than adhering to fixed growth rates, the adjusted model recognises that tourism growth is contextually influenced by health preparedness, which can vary significantly during health emergencies. Incorporating the IHR core capacity index further enhances the model's predictive

* Corresponding author.

E-mail addresses: mrodrigo-mail@gmx.com (M. Rodrigo), AjalaImene@uowdubai.ac.ae (I. Ajala), irhanida@kdupg.edu.my (A.K. Irhanida).

power regarding tourism responses to changing health landscapes.

Addressing the intersection of tourism and health preparedness can offer critical insights. The pandemic has demonstrated that a lack of readiness can severely impact tourist numbers. The modified model facilitates a quantitative analysis of this relationship, enabling destinations to manage health crisis risks more effectively. Furthermore, destinations exhibiting strong health preparedness may gain a competitive advantage, quickly regaining tourist confidence.

The potential implications of this revised model are profound. It informs policymakers on crisis management and encourages resilience-building strategies that bolster tourism amidst health challenges. Additionally, a holistic approach to tourism management fosters collaboration between health authorities and the tourism sector. By addressing some shortcomings of the traditional TALC model, the proposal offers valuable tools for navigating the complexities of tourism in a post-COVID world, enriching both academic discourse and practical strategies for sustainable tourism development.

This article is structured as follows. The literature review engages with the various facets of tourism sustainability post-COVID-19, emphasising health's role in this context. We then introduce a TALC model with a variable growth rate influenced by the IHR core capacity index, with properties summarised in the Appendix. Following this, we present an integration-based method for estimating parameters using tourist arrival and index data. The next section showcases model fitting results for New Zealand, China, Mexico, Colombia and Australia. Finally, we discuss the model and provide concluding remarks.

2. Literature review

Tourism is a complex global activity influenced by various economic, political, social, technological and environmental factors (Özkan & Boylu, 2021). Pre-COVID-19, key concerns included climate change, overtourism and sustainability issues, which were central to discussions among academics and policymakers (Boluk & Rasoolimanesh, 2022). The discourse on tourism has increasingly embraced the sustainable development paradigm outlined in the UN 2030 Agenda for Sustainable Development. The Sustainable Development Goals (SDGs) are pivotal in connecting tourism with sustainable development (Adie et al., 2022), highlighting the need to balance economic demands with our limited ecological resources (Boluk et al., 2019).

The UN 2030 Agenda for Sustainable Development aims 'to end poverty, protect the planet and ensure prosperity for all'. It highlights tourism's link to natural resource conservation, including marine resources, and emphasises the promotion of local products and culture (Hall, 2019). The SDGs underscore tourism's potential for sustainable development (Adie et al., 2022). The sustainability initiative of the UN World Tourism Organization (UNWTO) is framed through the One Planet Vision for the Responsible Recovery of the Tourism Sector, stressing that responsible recovery and resilience are inherently tied to sustainability (UNWTO, 2020). The Vision outlines six action areas: public health, social inclusion, biodiversity conservation, climate action, circular economy, and governance and finance (UNWTO, 2020).

Sustainable initiatives are emerging in response to escalating environmental crises like climate change and biodiversity loss. Issues arising from mass tourism, such as 'binge flying', the private sector's expansion through digital tools and the 'uberisation' of the economy, have prompted experts and governments to regulate tourism by adopting more ecologically and socially sustainable strategies (Boluk et al., 2019). Carrying capacity remains a key topic in discussions of tourism sustainability; see Boluk et al. (2019) and One Planet Network (2024) for further insights.

2.1. Tourism, sustainability and health crises

Infectious disease risks negatively affect tourism, particularly in developing countries where diseases are more prevalent and health

infrastructures are weaker (Cevik, 2022; Kruk, 2008; Novelli et al., 2018). Research on health crises and tourism in these regions is scarce, despite their vulnerability (Kruk, 2008; Novelli et al., 2018). Historically, there has been excessive focus on economic crises, with less attention to health-related impacts on tourism (Novelli et al., 2018).

The COVID-19 pandemic severely impacted a sector vital for economic growth in numerous countries (Boluk et al., 2019; Gao et al., 2021; Higgins-Desbiolles, 2021; Marome & Shaw, 2021; Novelli et al., 2018; Wut et al., 2021). The scale of the pandemic highlighted our societies' unpreparedness and vulnerability (Czabanowska & Kuhlmann, 2021; Sharfstein & Lurie, 2023). This situation occurred despite the WHO's calls for enhanced readiness following the 2014–2016 Ebola crisis, urging countries to develop robust, adaptive systems for rapid information gathering and expert mobilisation to prepare for potential pandemics (Khan et al., 2018).

The dynamics of the pandemic and policy responses are reflected in the significant revisions of COVID-19's impact on tourism by the UNWTO (Gössling et al., 2021). These revisions highlight the uncertainty surrounding COVID-19 and the resulting indecision in policy-making (Gössling et al., 2021). By May 2020, 163 out of 217 destinations had entirely halted international tourism (UNWTO, 2020). While tourism was adversely affected, it also facilitated the pandemic's spread, illustrating the complex interplay between these phenomena (Hoarau, 2022; Sharma et al., 2021). Countries with high tourist inflows experienced more COVID-19 cases, indicating that more globalised nations faced increased transmission rates (Farzanegan et al., 2021; Zimmermann et al., 2020).

This unprecedented health crisis has drawn renewed attention to the urgent need for sustainability, resilience and integrated approaches in the tourism industry (Boluk & Rasoolimanesh, 2022; Duro et al., 2023; Roxas et al., 2022). Recovery is now tied to reshaping practices that prioritise sustainability over merely increasing tourist numbers (Boluk & Rasoolimanesh, 2022; Gössling et al., 2021). Factors such as social distancing, new technologies, social entrepreneurship and heightened awareness of vulnerable populations may persist beyond the pandemic (Galvani et al., 2020). Thus COVID-19 offers an opportunity for transformative academic thinking about the positive integration of tourism and the SDGs (Boluk & Rasoolimanesh, 2022; Gössling et al., 2021; Higgins-Desbiolles, 2021; Marome & Shaw, 2021).

2.2. Enhancing health preparedness

A vital aspect of integrating SDGs into tourism is effective health crisis management. This involves not only securing the safety of tourists and local communities in the short term but also long-term recovery planning (Novelli et al., 2018). The UNWTO's One Planet Vision emphasises that responsible recovery and resilience in tourism must align with sustainability (UNWTO, 2020). Within this framework, the UNWTO has called for linking epidemiological indicators to tourism metrics to enhance preparedness (One Planet Network, 2024). Cooperation among tourism stakeholders, government authorities and scientific communities is crucial for developing protocols on hygiene, sustainability and communication measures (One Planet Network, 2024).

These interconnected demands present methodological challenges. The difficulty of making projections post-pandemic is well recognised (Gössling et al., 2021). Studies often focus on individual countries rather than adopting a systemic view, limiting understanding of the crisis. Hall et al. (2020) highlighted the scant literature and lack of longitudinal studies on pandemic–tourism links. Many studies consider only isolated impacts of COVID-19 using established methodologies based on general equilibrium theories (Roson & van der Vorst, 2023). However, life cycle models often lack precise trend data for various destinations (Hovinen, 2002). Epidemiological models typically neglect economic and social dimensions, particularly inequalities (Desai et al., 2020). A comprehensive understanding of COVID-19's impacts necessitates integrating

health consequences and socio-economic outcomes within a cross-sectoral framework (Desai et al., 2020). This multifaceted perspective can inform more effective governmental preparedness efforts that focus on both containment and socio-economic recovery (Desai et al., 2020; Sharfstein & Lurie, 2023). Merging epidemiology, health and economic indicators is essential for achieving this goal (Desai et al., 2020).

A significant methodological challenge in sustainable tourism lies in operationalising its definition and quantifying sustainability (Rasoolimanesh et al., 2023). An intriguing contribution is made by Gao et al. (2021), who examined sustainable tourism development in cities through the lens of the SDGs and a tourism competitiveness index. They acknowledged the limitations of their research and suggested that employing a quantitative approach to assess the impacts of COVID-19 on sustainable development could enhance crisis management and inform better social governance policies (Gao et al., 2021). Additionally, Yang et al. (2020) introduced a 'COVID19tourism index' that tracks the recovery process of the industry alongside the pandemic's broader effects. Duro et al. (2023) proposed a vulnerability index that integrates various indicators from domestic and international markets. Furthermore, Mertzanis and Papastathopoulos (2021) developed an epidemiological susceptibility risk index at the country level, which effectively predicts tourist flows, both inbound and outbound. Their research represents the first effort to link epidemiological susceptibility with tourism dynamics (Mertzanis & Papastathopoulos, 2021). Given that public health is a key element of sustainable tourism, further exploration of the relationship between health preparedness and tourism is warranted.

This article aims to contribute to ongoing debates by examining the link between pandemic preparedness and tourist numbers. Health preparedness remains a complex concept, difficult to define and measure (Khan et al., 2018; Nelson et al., 2007). The UN defines preparedness as the capacity of governments, professional response organisations, communities and individuals to foresee and effectively react to the effects of probable, impending or existing threats, events or situations (UNGHRP, 2020). The Sendai Framework for Disaster Risk Reduction 2015–2030, endorsed by the UN General Assembly, categorises pandemics as biological hazards and outlines four priorities: understanding disaster risk, strengthening governance, investing in, and enhancing preparedness for effective disaster response (Marome & Shaw, 2021; UNDRR, 2024). According to Nelson et al. (2007), public health emergency preparedness refers to the ability of public health and healthcare systems, along with communities and individuals, to effectively prevent, protect against, respond swiftly to, and recover from health emergencies. This is particularly crucial for emergencies characterised by their scale, timing or unpredictability, which can overwhelm standard operational capabilities. Preparedness can be understood through the interactions among structures, processes and outcomes (Nelson et al., 2007). Petrović et al. (2020) utilised an integrated framework that emphasised readiness structure and reaction processes across three dimensions: institutional, medical and societal. Emergency public health preparedness should be viewed holistically, involving not just the health sector, but society as a whole (Petrović et al., 2020). This cross-societal perspective, from a governance standpoint, requires partnerships among various stakeholders and efficient coordination, particularly regarding disaster risk management, to better serve local communities and develop more effective emergency preparedness strategies (Gamboa-Maldonado et al., 2012; Khan et al., 2018; Marome & Shaw, 2021; Sharfstein & Lurie, 2023; UNDRR, 2024; Wut et al., 2021).

Though public health emergency preparedness frameworks exist, they lack empirical grounding and consensus on standards (Khan et al., 2018; Nelson et al., 2007). The public health competency framework launched by the WHO and Association of Schools of Public Health in the European Region (ASPHER) aims to strengthen the health workforce's pandemic readiness, encompassing five dimensions: flexibility, research, epidemiology, preparedness and employability (Czabanowska & Kuhlmann, 2021). Following the COVID-19 pandemic, the European Union established the EU Health Emergency Preparedness and Response

Authority (HERA) in September 2021 to enhance Europe's response and medical countermeasures during health crises, addressing prior shortcomings in preparedness and medical supplies (Wouters et al., 2023).

2.3. International health regulations

The IHR are vital to global health security, providing a legal framework for the international community to address public health risks (Caldera et al., 2023). The 13 core capacities assess country-level preparedness for health crises, focusing on legislation, financing, coordination, communication and sensitive sites (e.g. laboratories, zoonotic and chemical events, radionuclear emergencies) (WHO, 2023). The main objectives are to prevent and control the international spread of diseases through improved monitoring, alert systems and collaboration (Burci, 2020). States are responsible for implementing these measures nationally (Caldera et al., 2023). However, few countries fully comply with the IHR, leaving many destinations ill-prepared for infectious disease management (Mertzanis & Papastathopoulos, 2021). Numerous articles highlight the IHR's limitations, revealed during the COVID-19 pandemic, such as inadequate international cooperation, insufficient core capacities and challenges in unified implementation due to the WHO's lack of enforcement authority (Bartolini, 2021; Broberg, 2020; Burci, 2020; Cockerham, 2022; Razum & Bozorgmehr, 2020; Zhou et al., 2020). There have been calls for reforms to the IHR's institutional design to enhance enforcement capabilities (Bartolini, 2021; Blinken & Becerra, 2021; Burci, 2020; Cockerham, 2022). Nonetheless, the IHR remain central to public health safety, and the core capacity index, which collects longitudinal data, is valuable for testing our model.

In conclusion, the COVID-19 pandemic has emphasised the importance of sustainable tourism. As the sector recovers, there is an accelerated push for environmentally respectful, community-empowering and future-friendly policies. This complex pursuit requires diverse methodological approaches, including quantitative methods (Rasoolimanesh et al., 2023). While existing literature may not directly connect health and sustainable tourism, we assert that health infrastructure is vital for tourism resilience, especially following crises like COVID-19. Our aim is to broaden the dialogue on sustainable tourism by emphasising health considerations, aligning with the SDGs. By using the IHR core capacity index, we demonstrate that improved health readiness can sustain visitor numbers and indelibly strengthen sustainability. This literature review highlights initiatives that quantitatively address sustainable tourism concepts, including health implications (Duro et al., 2023; Mertzanis & Papastathopoulos, 2021; Yang et al., 2020). This article focuses on the health aspect of sustainability, contributing to the discussion by adapting Butler's seminal model to explore the interconnection between tourism and country-level health preparedness via the IHR core capacity index. The following section offers a precise formulation of the model.

3. Model formulation

The TALC logistic model is described by the differential equation

$$\frac{dT}{dt} = rT \left(1 - \frac{T}{K} \right), \quad (3.1)$$

where $T = T(t)$ represents the number of tourists at time t and $\frac{dT}{dt}$ is its rate of change. The constants r and K denote the growth rate and tourist carrying capacity, respectively (Kraja & Beshiri, 2019; Lundtorp & Wanhill, 2001). A negative growth rate leads to a decline in tourist numbers if below capacity.

We assume the growth rate depends on a nonnegative index $I = I(t)$, modifying Eq. (3.1) to

$$\frac{dT}{dt} = r(I)T \left(1 - \frac{T}{K} \right). \quad (3.2)$$

For small I , we have $r(I) < 0$, indicating a decrease in the population. A critical index level I^* exists beyond which $r(I)$ becomes positive and the population increases. Thus assume that $r(I) < 0$ for $0 \leq I < I^*$ and $r(I) > 0$ for $I > I^*$. It follows that

$$r(0) < 0, \quad r(I^*) = 0, \quad r'(I^*) > 0. \tag{3.3}$$

A simple example for $r(I)$ is

$$r(I) = c(I - I^*), \quad c > 0. \tag{3.4}$$

Let $a, b > 0$ be constants. Assume that the index rate of change $\frac{dI}{dt}$ is proportional to the index level for small times (modelled by aI) but decreases due to ‘interaction’ with the tourist population (modelled by bTI). Thus the index dynamics are described by the differential equation

$$\frac{dI}{dt} = aI - bTI = I(a - bT). \tag{3.5}$$

Observe that the index level goes down ($\frac{dI}{dt} < 0$) when the tourist population is sufficiently large ($T > \frac{a}{b}$).

Combining Eqs. (3.2) and (3.5), a TALC model that incorporates an index-dependent growth rate is represented by the system

$$\frac{dT}{dt} = r(I)T \left(1 - \frac{T}{K}\right), \tag{3.6a}$$

$$\frac{dI}{dt} = I(a - bT). \tag{3.6b}$$

The rest of this section summarises some properties of (3.6); detailed derivations are provided in the Appendix.

Model (3.6) can apply to other indices with modifications to the growth rate function and dynamics. Here, we consider the IHR core capacity index for examining public health preparedness versus tourist numbers: inadequate preparedness (I small) yields $r(I) < 0$, decreasing tourists, while adequate preparedness (I large) gives $r(I) > 0$, thus increasing tourists.

3.1. Interpretation of the model parameters in a TALC context

Parameter a indicates the rate at which index I increases relative to its current level. A higher a signifies a stronger positive self-influence, fostering index growth as tourism develops. It encapsulates the index’s ability to ‘self-boost’ under favourable conditions, reflecting how rapidly it can improve during growth phases. In contrast, parameter b captures the negative impact of the tourist population T on index I . It quantifies the strain tourists place on local resources, such as infrastructure and health services, resulting in a decline in the index at higher tourist numbers. A larger b denotes a more significant detrimental effect, highlighting issues like overcrowding and resource depletion from sustained tourism growth.

The function $r(I)$ is vital for analysing how changes in the index affect tourism. When $0 \leq I < I^*$, poor social conditions and unpreparedness lead to fewer tourists, often due to societal problems, geopolitical instability or health crises. At $I = I^*$, the index marks a shift to favourable tourism conditions, typically from significant investments in public health, safety or infrastructure. When $I > I^*$, adequate readiness promotes tourism growth, creating a positive feedback loop where increased tourist numbers enhance the index through higher revenue and initiatives.

The relationship between tourist dynamics and index growth, as shown in Eq. (3.6b), indicates that rising tourist numbers T can put pressure on local resources, services and health systems, adversely affecting the index I . This impact is more pronounced during peak seasons or crises, when demand outstrips supply. Moreover, a high tourist population can diminish both visitor experiences and local quality of life, creating a negative feedback loop where deteriorating conditions lower I and subsequently reduce T .

The implications of model (3.6) apply to various real-world situations. In public health preparedness during pandemics like COVID-19, initial conditions can lead to a steep decline in tourism due to health risks. Policymakers should aim to increase the index I through vaccination campaigns, awareness initiatives and infrastructure improvements. In ecotourism, managing the tourist variable T is crucial for protecting local ecosystems, which can sustain and enhance tourist interest over time. Finally, the model serves as a framework for crisis management, helping authorities decide whether to promote or restrict tourism based on current index levels.

These findings emphasise the importance of monitoring and managing both T and I in tourism management. Regions can boost investment in infrastructure and safety measures to enhance their I , ensuring stable growth for T . Ongoing assessment of both indices allows for timely policy adjustments to prevent declines in tourism.

3.2. Determination and interpretation of the equilibria

There are three equilibria (T_∞, I_∞) of (3.6), specifically

$$P_1 = (0, 0), \quad P_2 = (K, 0), \quad P_3 = \left(\frac{a}{b}, I^*\right). \tag{3.7}$$

Equilibria P_1 and P_2 correspond to steady states $T_\infty = 0$ (no tourists) and $T_\infty = K$ (tourist population at carrying capacity) in the constant growth rate logistic model Eq. (3.1). Steady state P_3 represents a ‘coexistence’ state, as per population ecology terminology (Brauer & Castillo-Chávez, 2012).

Table 1 summarises the steady state analysis in Appendix A. Note that P_3 (when $K > \frac{a}{b}$) is a ‘non-robust’ case, as linear stability analysis does not provide sufficient information on its classification and stability. We will later demonstrate that this steady state is a nonlinear centre and thus stable (but not asymptotically stable). Since P_1 and P_2 are unstable, P_3 (when $K > \frac{a}{b}$) becomes the relevant steady state in our model and will be the focus of the discussion.

Phase portraits of (3.6) generated using pplane are shown in Fig. 1 (when $K < \frac{a}{b}$) and Fig. 2 (when $K > \frac{a}{b}$). The horizontal and vertical axes are T and I , respectively. The blue curves represent solution trajectories of (3.6) for different initial conditions (T_0, I_0) . The nullclines are in yellow and orange, the equilibria are shown as orange dots and the direction field is drawn as green arrows.

As seen in Figs. 1 and 2, the trajectories of (3.6) in the TI -plane appear complicated. Nevertheless, the equation they satisfy can be obtained. It is shown in Appendix B that trajectories of (3.6) (i.e. the blue curves in Figs. 1 and 2) satisfy a nonlinear equation in T and I . In Appendix C, it is shown that the equation of the trajectories near P_3 can be approximated by an ellipse. Thus P_3 is a nonlinear centre of (3.6), so that $T(t)$ and $I(t)$ are periodic in t . It can be verified in Fig. 2 that indeed the solution curves near P_3 are closed.

A profile of a periodic solution $(T(t), I(t))$ vs t obtained by directly solving (3.6) numerically is shown in Fig. 3, where $r(I)$ in Eq. (3.4) is chosen. Take $c = 0.01$, $I^* = 5$, $K = 10$, $a = 0.2$, $b = 0.1$ and $(T_0, I_0) = (3, 10)$. Note that $K = 10 > 2 = \frac{a}{b}$, consistent with Table 1.

Remark 3.1. Within the context of a TALC, the significance of periodic solutions is that rejuvenation or decline during the poststagnation stage is taken into account; see the rise and fall of the tourist population in Fig. 3a. This is not possible in the logistic model Eq. (3.1) since the

Table 1
Classification and stability of equilibria of (3.6).

Steady state	$K < \frac{a}{b}$	$K > \frac{a}{b}$
$P_1 = (0, 0)$	unstable saddle point	unstable saddle point
$P_2 = (K, 0)$	unstable node	unstable saddle point
$P_3 = \left(\frac{a}{b}, I^*\right)$	unstable saddle point	linear centre

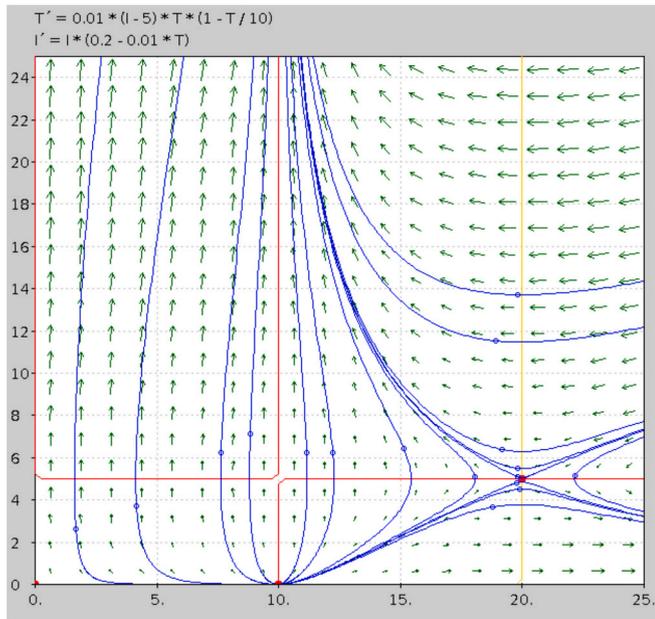


Fig. 1. Phase portrait of (3.6) with $c = 0.01$, $I^* = 5$, $K = 10$, $a = 0.2$ and $b = 0.01$. Note that $K = 10 < 20 = \frac{a}{b}$.

growth rate is constant there. Similarly behaving periodic solutions are also encountered in the Lotka–Volterra prey–predator system (Brauer & Castillo-Chávez, 2012).

4. Calibrating the model: an integration-based method for parameter estimation

Next, we develop an integration-based method to estimate the parameters in a model described by a system of differential equations, as developed in Holder and Rodrigo (2013); Zulkarnaen and Rodrigo (2020). This approach is especially useful when the analytical solution of the system cannot be obtained or when there are many parameters to estimate.

Assume for the moment that $T(t)$ and $I(t)$ are known for all $t \in [t_i, t_f]$, where the initial time t_i is less than the final time t_f . Take the growth rate function Eq. (3.4). Assume also for now that K is known. We wish to estimate c , I^* , a and b in (3.6).

We can rewrite Eqs. (3.6a) and (3.6b) as

$$\frac{dT}{dt} = cIT \left(1 - \frac{T}{K}\right) - c^* T \left(1 - \frac{T}{K}\right) \tag{4.1}$$

and

$$\frac{dI}{dt} = aI - bIT, \tag{4.2}$$

respectively. Both are particular cases of

$$\dot{h}(t) = c_1 h_1(t) + c_2 h_2(t), \tag{4.3}$$

where $\dot{(\)}$ denotes differentiation with respect to t . In Eq. (4.1), we identify

$$h(t) = T(t), \quad h_1(t) = I(t)T(t) \left[1 - \frac{T(t)}{K}\right], \quad h_2(t) = T(t) \left[1 - \frac{T(t)}{K}\right], \quad c_1 = c, \quad c_2 = -c^*,$$

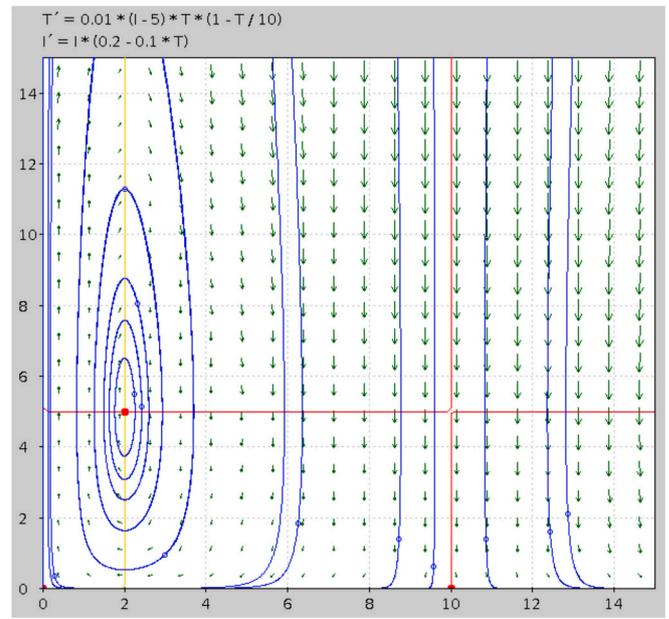


Fig. 2. Phase portrait of (3.6) with $c = 0.01$, $I^* = 5$, $K = 10$, $a = 0.2$ and $b = 0.1$. Note that $K = 10 > 2 = \frac{a}{b}$.

while in Eq. (4.2), we have

$$h(t) = I(t), \quad h_1(t) = I(t), \quad h_2(t) = I(t)T(t), \quad c_1 = a, \quad c_2 = -b.$$

here, h , h_1 and h_2 are assumed known; the goal is to estimate c_1 and c_2 . In Appendix D, it is shown that (c_1, c_2) is the solution of algebraic linear system

$$\begin{aligned} (Ah)(s_0) &= c_1(Ah_1)(s_0) + c_2(Ah_2)(s_0), \\ (Ah)'(s_0) &= c_1(Ah_1)'(s_0) + c_2(Ah_2)'(s_0), \end{aligned} \tag{4.4}$$

where A is some integral operator and s_0 is a chosen convenient value (e.g. $s_0 = 0$).

Remark 4.1. In reality, $T(t)$ and $I(t)$ are not available for all $t \in [t_i, t_f]$. Instead, they are given at discrete time values, say $\{(t_j, T_j)\}$ and $\{(t_j, I_j)\}$, where $t_1 = t_i$, $t_n = t_f$ and $j = 1, 2, \dots, n$. To evaluate the integrals in Eq. (4.4), we apply a numerical quadrature technique, e.g. integration by spline interpolation.

5. Numerical simulations using empirical data

The algorithm for estimating the parameters in (3.6) is as follows:

1. Obtain the tourist population data set $\{(t_j, T_j)\}$ and the index data set $\{(t_j, I_j)\}$.
2. Pick a weighting function w , e.g. $w(t, s) = e^{-st}$, and let $s_0 = 0$.
3. Estimate the maximum tourist population from the data set, then fix a value for K greater than or equal to the maximum.
4. Solve Eq. (4.4) for c_1 and c_2 , using

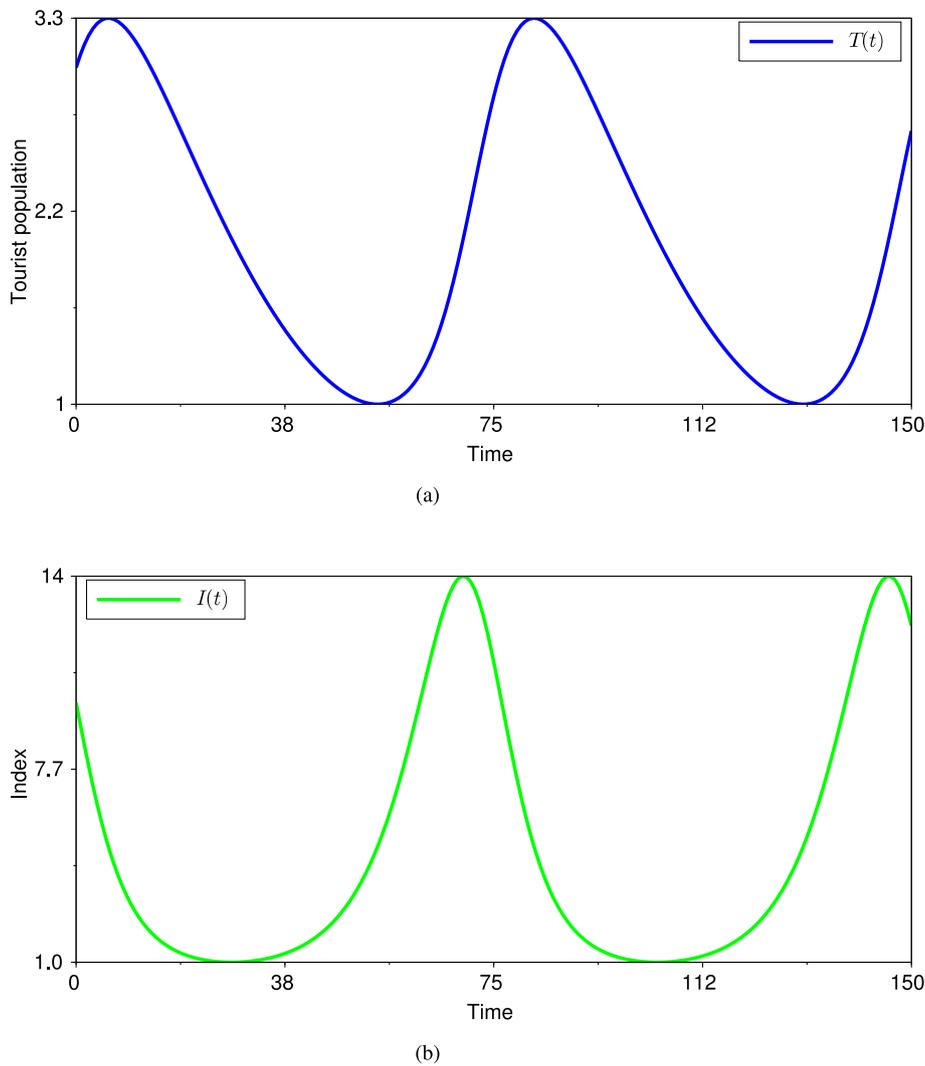


Fig. 3. Profile of the periodic solution of (3.6) ($T(t)$ vs t in (a) and $I(t)$ vs t in (b)) when $c = 0.01$, $I^* = 5$, $K = 10$, $a = 0.2$, $b = 0.1$, $T_0 = 3$ and $I_0 = 10$ (with $K = 10 > 2 = \beta$). The rise and fall of the tourist population captures the poststagnation stage.

$$h(t) = T(t), \quad h_1(t) = I(t)T(t) \left[1 - \frac{T(t)}{K} \right], \quad h_2(t) = T(t) \left[1 - \frac{T(t)}{K} \right].$$

$$\text{Set } \hat{c} = c_1 \text{ and } \hat{I} = -\frac{c_2}{c_1}.$$

5. Solve Eq. (4.4) for c_1 and c_2 , using

$$h(t) = I(t), \quad h_1(t) = I(t), \quad h_2(t) = I(t)T(t).$$

$$\text{Set } \hat{a} = c_1 \text{ and } \hat{b} = -c_2.$$

6. Solve (3.6) numerically from $t = t_1$ to $t = t_n$ using the estimated parameters \hat{c} , \hat{I} , \hat{a} and \hat{b} . Denote the numerical solution by $\{(t_j, \hat{T}_j, \hat{I}_j)\}$.

7. Compute the ‘distance’ between the numerical solution in step 6 and the given data in step 1 using the root mean square error (RMSE):

$$\text{RMSE}(K) = \left\{ \frac{1}{n} \sum_{j=1}^n \left[\left(\frac{T_j - \hat{T}_j}{K} \right)^2 + (I_j - \hat{I}_j)^2 \right] \right\}^{\frac{1}{2}}.$$

8. Repeat steps 3–7 for different values of K and take the set of parameter estimates that yields the smallest $\text{RMSE}(K)$.

Remark 5.1. In a typical least squares approach, (3.6) would be solved numerically as K , c , I^* , a and b are made to vary over a region in five-dimensional state space. Then an analogous root mean square error function of five variables is defined and minimised over the region. However, this approach is costly and it is not obvious what a feasible region should be. In contrast, our proposed algorithm varies only K and the root mean square error function is minimised with respect to K only. The parameters c , I^* , a and b can be calculated, for each given K , from the linear system Eq. (4.4).

Data are collected by the UNWTO through a series of yearly questionnaires that are in line with the International Recommendations for Tourism Statistics (IRTS 2008) standard led by the UNWTO and approved by the United Nations. A spreadsheet of (incomplete) inbound tourism data, grouped by country for 1995–2022, is available from the UNWTO website (UNWTO, 2024). We choose to utilise inbound tourism data due to its greater accessibility compared to domestic tourism data, which can be limited or unavailable in certain countries. This approach also ensures consistency in our analysis across the various countries included in the simulations. Qualitatively, we do not anticipate significant differences in the results. As for IHR compliance, estimates by country for 2010–2020 can be obtained from the WHO website (WHO, 2024). Note that the IHR index data given in WHO (2024) are only

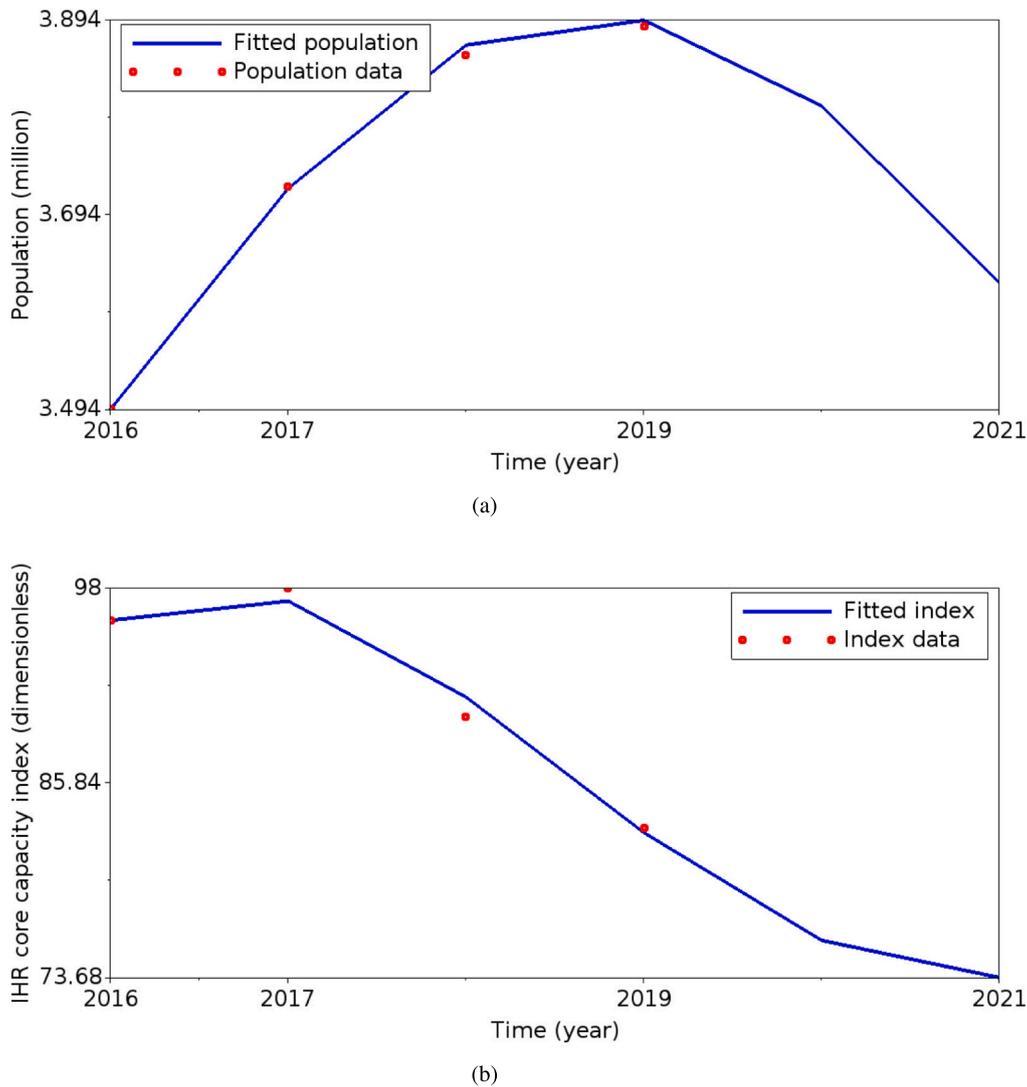


Fig. 4. UNWTO tourist arrival and IHR core capacity index data for New Zealand, together with the numerical solution of (3.6) with $\hat{K} = 4.5000$, $\hat{c} = 0.0262$, $\hat{I} = 85.1486$, $\hat{a} = 1.4213$ and $\hat{b} = 0.3903$ (minimum error is $RMSE(\hat{K}) = 0.7335$).

available until 2020. To make the ranges for the UNWTO tourist data and the IHR core capacity index overlap, we consider subintervals in the range 2010–2019, disregarding the values in 2020 as these are outliers due to the pandemic that would skew the fitting. The IHR index data are not complete for many countries even in the range 2010–2019; hence subintervals in this range are sometimes considered.

Consider the case of New Zealand in Fig. 4. The algorithm is implemented for each K (in million) in the interval $[3, 5]$ in increments of $\Delta K = 0.1$. The minimum value of $RMSE(K)$ is 0.7335, obtained when $\hat{K} = 4.5000$. The estimated parameter values from steps 4 and 5 are $\hat{c} = 0.0262$, $\hat{I} = 85.1486$, $\hat{a} = 1.4213$ and $\hat{b} = 0.3903$. The red dots in Fig. 4a and b represent the tourist and index data, respectively. The blue curves in Fig. 4a and b represent the components $T(t)$ and $I(t)$ for $2016 \leq t \leq 2021$, respectively, of the numerical solution of (3.6) using the estimated parameters. Note that (3.6) is solved until 2021 to observe the general trend post-2019.

Following analogous descriptions of the numerical results given above for Fig. 4, the corresponding results are also shown for China (see Fig. 5), Mexico (see Fig. 6), Colombia (see Fig. 7) and Australia (see Fig. 8).

6. Discussion

Risks for the tourism industry have been exacerbated in recent years by more occurrences of infectious diseases and environmental disruptions due to climate change, representing high economic and social costs (Duro et al., 2023; Mertzanis & Papastathopoulos, 2021), pushing further the need for sound monitoring and predictive models and tools to face future shocks. One of the main strengths of the TALC model is precisely the idea that destinations may experience decline if suitable decisions are not made at the strategic level when it comes to planning (Hovinen, 2002). Our modified TALC model highlights not only the links between health preparedness and the tourist population but also factors in the maximum tourist level, a crucial parameter which should be more prominently taken into account for planning purposes. This means that public health preparedness, in contexts which heavily depend on tourist flows and income, should consider data models to better identify the threshold, defined by the maximum tourist level, which starts endangering even an optimal health preparedness. This emphasises again the importance of the carrying capacity, the main metric to determine the limits of development and optimal use of tourism resources (Mihalic, 2020). The establishment of maximum operating and carrying capacity limits is relatively straightforward to help determine the limits of growth (Namberger et al., 2019; Oklevik et al., 2019) but can be difficult to

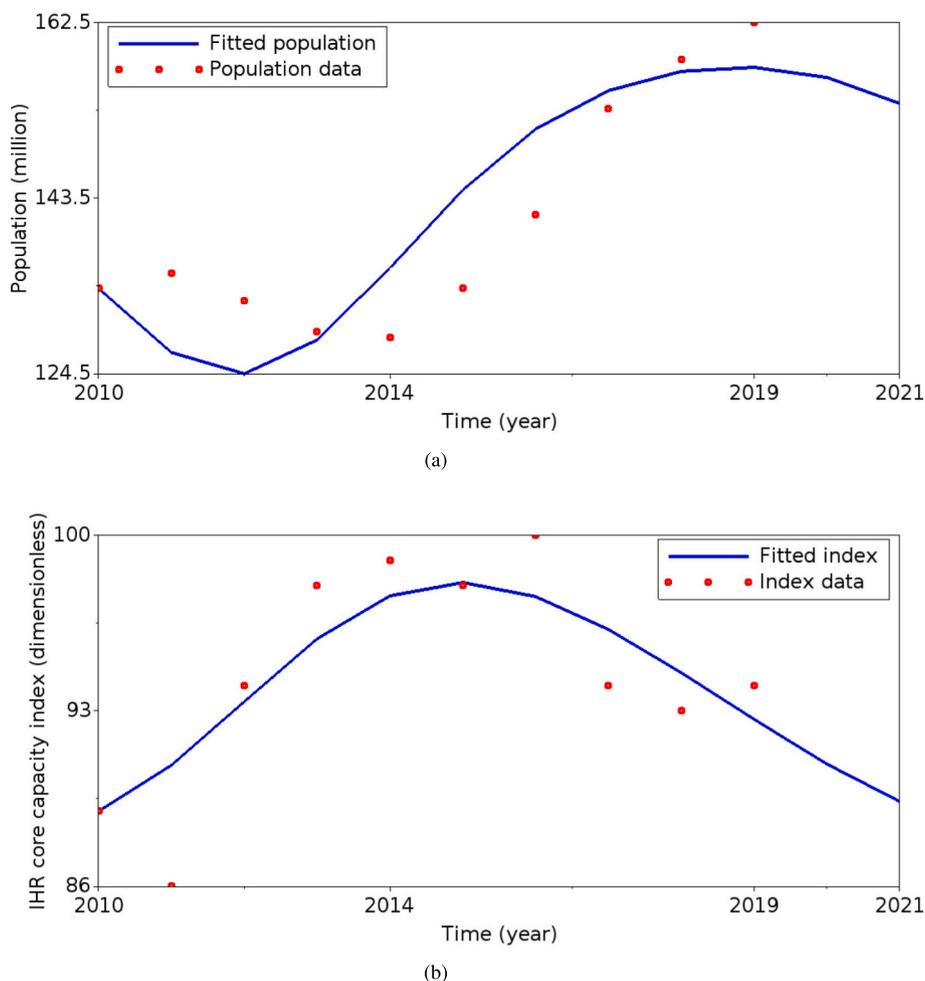


Fig. 5. UNWTO tourist arrival and IHR core capacity index data for China, together with the numerical solution of (3.6) with $\hat{K} = 170.0000$, $\hat{c} = 0.0707$, $\hat{I}^* = 93.0683$, $\hat{a} = 0.2104$ and $\hat{b} = 0.0015$ (minimum error is $RMSE(\hat{K}) = 2.1307$).

measure and implement beyond specific locations (Butler & Dodds, 2022). Namberger et al. (2019) identify six forms of carrying capacity: physical, environmental, economic, infrastructural, perceptual and social. Considering a health or sanitary carrying capacity depending on the readiness of health infrastructures can help stakeholders be more prepared to manage the consequences of pandemics in tourism destinations. Proactive measures to mitigate the impact of pandemics on the tourism industry can build a stronger resilience (Sharma et al., 2021). Adaptive management through mechanisms for quick policy adjustments, industry support and comprehensive communication strategies can enable swift adjustments in the face of the unforeseen.

The various interpretations of ‘sustainable tourism’ have significant implications, especially following the COVID-19 pandemic, which highlighted the vital link between health preparedness and the sustainability of tourism destinations. Our article emphasises the importance of integrating health infrastructure into the broader discourse of sustainable tourism, as destinations with robust health systems are better equipped to manage disruptions and maintain visitor numbers.

Utilising an index-dependent growth rate in the modified TALC model allows us to quantitatively demonstrate how enhancements in health readiness—measured by the IHR core capacity index—directly contribute to the viability of tourism. By establishing this connection, we seek to expand the definition of sustainable tourism to include essential health considerations that foster resilience in the sector, alongside environmental and social dimensions.

The proposed modified TALC model has crucial practical and policy implications for tourism management and public health preparedness.

By incorporating health preparedness indicators, particularly the IHR core capacity index, the model shifts from traditional growth metrics to prioritising health safety during infectious disease outbreaks and other crises.

Practically, this adaptation encourages destination managers to adopt proactive planning and management strategies that foster resilience through integrated health measures. By leveraging the IHR index, stakeholders can evaluate their readiness for health crises, ensuring informed decision-making aligned with public health strategies. Destinations can enhance adaptive capacity by developing flexible operational protocols, including staff training and communication frameworks.

From a policy standpoint, integrating health considerations into tourism policies—such as travel restrictions and health screenings—can bolster tourist confidence. Policymakers should utilise ongoing research to analyse data pertinent to health and tourism, facilitating proactive responses to potential health risks.

However, challenges like data availability, funding constraints and stakeholder engagement may impede implementation. The modified TALC model ultimately advocates for a comprehensive approach to tourism that prioritises health and safety alongside economic objectives, ensuring sustainable practices for the future.

A more quantitative discussion is as follows. Using the parameter estimates for the five countries considered above, it can be verified that $K > \frac{a}{b}$ holds. Hence $P_3 = (\frac{a}{b}, I^*)$ is a nonlinear centre of (3.6) in each of the countries. As shown in Appendix C, solution curves of Eq. (B.1) near

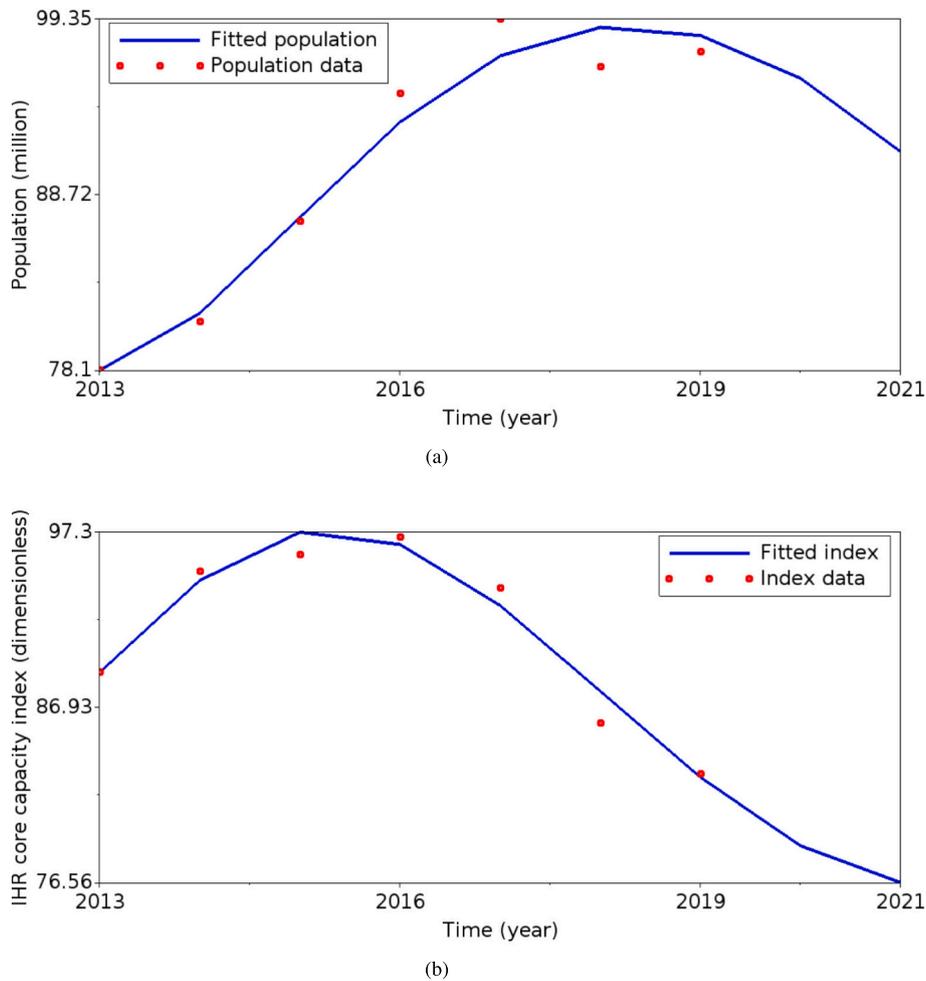


Fig. 6. UNWTO tourist arrival and IHR core capacity index data for Mexico, together with the numerical solution of (3.6) with $\hat{K} = 120.0000$, $\hat{c} = 0.0240$, $\hat{I} = 86.4708$, $\hat{a} = 0.5524$ and $\hat{b} = 0.0062$ (minimum error is $RMSE(\hat{K}) = 0.9902$).

P_3 are closed; therefore $T(t)$ and $I(t)$ are periodic in t . This captures the decline in tourist arrivals in the poststagnation stage, which is not present in the TALC logistic model Eq. (3.1), using actual tourist arrival data.

As mentioned previously, periodic solutions are also found in the Lotka–Volterra prey–predator model (Brauer & Castillo-Chávez, 2012)

$$\frac{dx}{dt} = ax - bxy,$$

$$\frac{dy}{dt} = -cy + dxy,$$

where $x(t)$ (respectively, $y(t)$) is the prey (respectively, predator) population at time t , and a, b, c , and d are positive constants. When the predator population is low (small y), $\frac{dx}{dt} \simeq ax$ and the prey population increases. When the prey population is low (small x), $\frac{dy}{dt} \simeq -cy$ and the predator population decreases. Thus, starting with small prey and predator populations, the prey population first increases due to little predation, and then the predator population increases due to abundant food. This leads to heavier predation and a decrease in prey. As a result, the predator population decreases and the system returns to its original state. Defining $f(x, y) = ax - bxy$ and $g(x, y) = -cy + dxy$, we see that $D_2f(x, y) = -bx < 0$ and $D_1g(x, y) = dy > 0$. The difference in signs characterises prey–predator dynamics (Brauer & Castillo-Chávez, 2012; Rodrigo et al., 2023).

It is interesting to extend the analogy to (3.6) by identifying the ‘prey’ and ‘predator’. Indeed, if T and I are initially small, then Eq.

(3.6b) can be approximated by $\frac{dT}{dt} \simeq aI$ and the index first increases. Moreover, since $T^2 \ll T$ and $r(I) \simeq r(0) + r'(0)I \simeq r(0) < 0$, then Eq. (3.6a) can be approximated by $\frac{dI}{dt} \simeq r(0)T$ and the tourist population first

decreases. Defining $f(T, I) = r(I)T \left(1 - \frac{T}{K}\right)$ and $g(T, I) = I(a - bT)$, then

$D_2f(T, I) = r'(I)T \left(1 - \frac{T}{K}\right)$ and $D_1g(T, I) = -bI$. If $r'(I) > 0$ (the growth rate function is always increasing, as is the case in Eq. (3.4)) and $T < K$ (the tourist population has not reached its carrying capacity), then $D_2f(T, I) > 0$ and $D_1g(T, I) < 0$. Hence we observe ‘prey–predator’ dynamics in (3.6), where the tourist population is the ‘predator’ and the index is the ‘prey’.

Next, consider the average number of tourists and the average growth rate. We continue to consider solutions of (3.6) in the periodic regime, i.e. closed curves of Eq. (B.1) near P_3 (when $K > \frac{a}{b}$). If P is the period and t_0 is some arbitrary initial time, then the average number of tourists and the average growth rate over $[t_0, t_0 + P]$ is defined by the standard continuous averages

$$T_{ave} = \frac{1}{P} \int_{t_0}^{t_0+P} T(t) dt \quad \text{and} \quad r_{ave} = \frac{1}{P} \int_{t_0}^{t_0+P} r(I(t)) dt, \quad (6.1)$$

respectively. It is shown in Appendix E that

$$\frac{1}{P} \int_{t_0}^{t_0+P} T(t) dt = \frac{a}{b} \quad \text{and} \quad \frac{1}{P} \int_{t_0}^{t_0+P} r(I(t)) dt = 0.$$

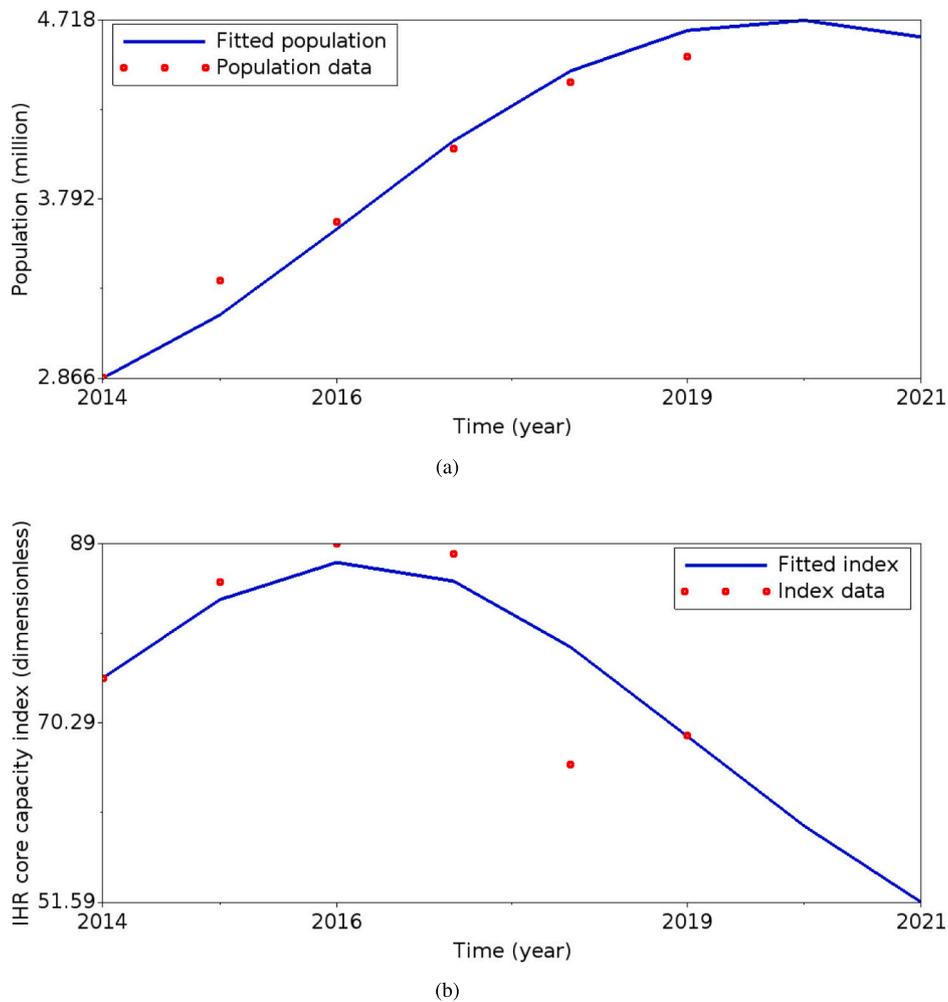


Fig. 7. UNWTO tourist arrival and IHR core capacity index data for Colombia, together with the numerical solution of (3.6) with $\hat{K} = 7.0000$, $\hat{c} = 0.0103$, $\hat{I} = 60.8439$, $\hat{a} = 0.5501$ and $\hat{b} = 0.1480$ (minimum error is $RMSE(\hat{K}) = 5.2437$).

Hence the average growth rate r_{ave} , as defined in Eq. (6.1), is zero. An analogous expression for the average index $I_{ave} = \frac{1}{P} \int_{t_0}^{t_0+P} I(t) dt$ is possible if the growth rate function $r(I)$ is specified. Indeed, if $r(I)$ is given by Eq. (3.4), then

$$I_{ave} = \frac{1}{P} \int_{t_0}^{t_0+P} I(t) dt = I^*$$

In summary, we offer the interpretation that $\frac{a}{b}$ represents the average tourist population T_{ave} and I^* is the average index I_{ave} , both over any interval of time of length P . Referring to Eq. (3.6b), when the tourist population rises above the average tourist population (i.e. $T > T_{ave} = \frac{a}{b}$), then the index will decrease (i.e. $\frac{dI}{dt} < 0$). That is, sufficiently large tourist numbers leads to a ‘less adequate’ public health preparedness according to the model. Looking at Eq. (3.6a), if the index rises above the average index (i.e. $I > I_{ave} = I^*$), then the tourist population will increase (i.e. $\frac{dT}{dt} > 0$), provided it is below the carrying capacity (i.e. $T < K$). Thus ‘sufficiently adequate’ public health preparedness contributes to an increase in tourist numbers as long as the maximum tourist level has not been reached.

As seen in Figs. 4–8, (3.6) predicts a decline in the tourist population after 2019, which we know actually occurred because of the COVID-19 pandemic. However, the actual tourist arrival numbers in 2020 are of course much lower than those predicted by (3.6). We do not claim that our model has precise predictive capabilities, but rather it describes the general qualitative behaviour of both the tourist population and the core

capacity index. The main objective of the paper is still to put forward a model that is able to capture the decline or rejuvenation trends in the poststagnation stage through periodic solutions.

7. Conclusion

In this article, we present a modified version of Butler’s TALC model, incorporating an index-dependent growth rate to better reflect the dynamics between public health preparedness and tourism flows. The COVID-19 pandemic has underscored the critical interplay between health infrastructure and the tourism sector, necessitating a reevaluation of existing frameworks. Our research utilises the IHR core capacity index as a proxy for health preparedness, alongside tourist arrival data from the UNWTO. This integration allows us to analyse the effects of health preparedness on tourist dynamics in a post-pandemic context.

While we acknowledge that the growth rate is influenced by public health preparedness, we also recognise the significant role of various other factors, such as the outbound tourism policies of source countries. Consequently, our next step in the modelling process will involve treating the growth rate as a function of multiple indices that quantify these additional factors. Rather than introducing a single differential equation as shown in Eq. (3.6b), we will develop a series of differential equations that capture the dynamics of each of these indices. This approach will undoubtedly increase the complexity of the mathematical analysis and model fitting.

The reformulated TALC model provides valuable theoretical

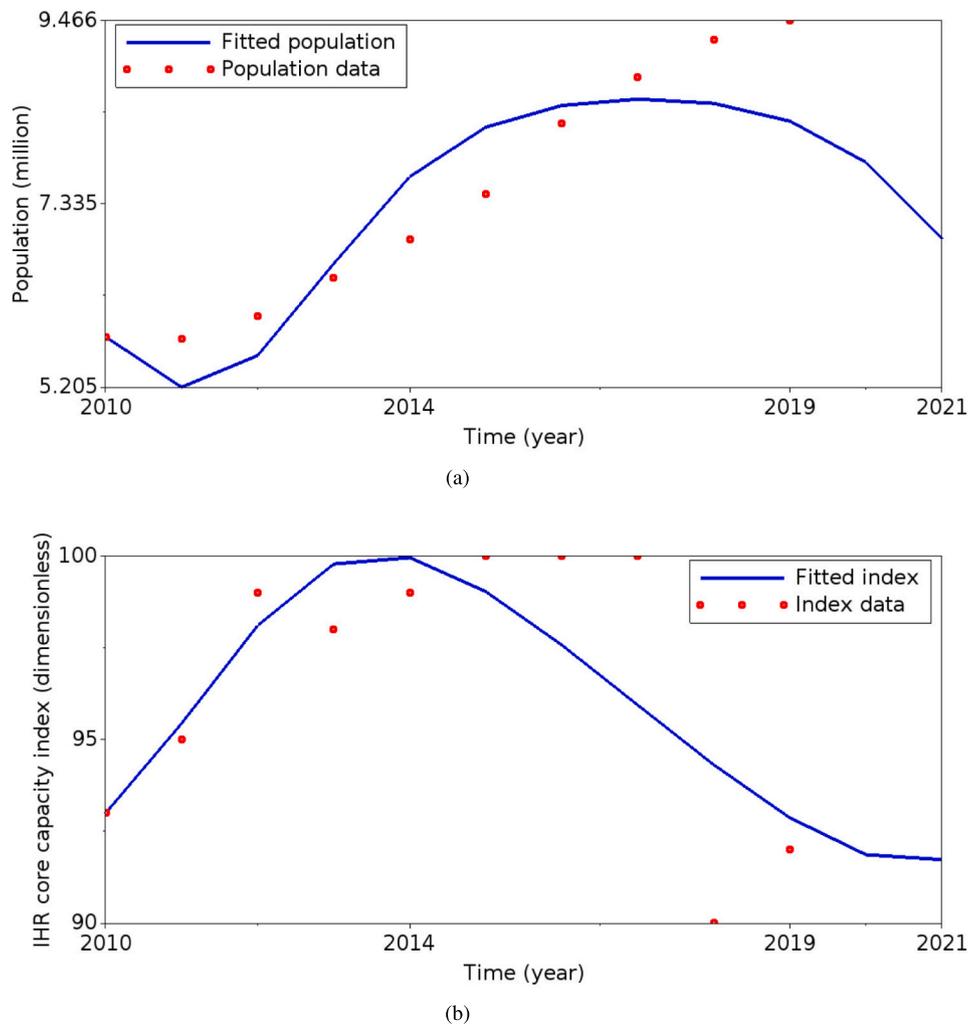


Fig. 8. UNWTO tourist arrival and IHR core capacity index data for Australia, together with the numerical solution of (3.6) with $\hat{K} = 9.0000$, $\hat{c} = 0.1671$, $\hat{I} = 95.7934$, $\hat{a} = 0.1010$ and $\hat{b} = 0.0138$ (minimum error is $RMSE(\hat{K}) = 2.1858$).

implications, challenging traditional tourism frameworks that neglect the impact of health metrics. By integrating health preparedness into the tourism growth framework, our model prompts further investigation into additional factors, such as environmental and economic indices, that influence tourism resilience. This comprehensive approach enhances the robustness of the model, inviting future research to explore the dynamics of risk perceptions, as indicated by Mertzanis and Papastathopoulos' epidemiological susceptibility risk index (Mertzanis & Papastathopoulos, 2021), which may affect destination life cycles and tourist behaviour.

From a practical standpoint, the modified TALC model serves as an essential tool for policymakers and tourism managers aiming to navigate the complexities of crisis management. Acknowledging that increased tourist numbers can both strain health resources and contribute to enhanced preparedness is critical. The IHR core capacity index offers a quantifiable measure for assessing national health systems, guiding policymakers in terms of investment and resource allocation. By adopting this model, decision-makers can strategically manage tourist levels, enhance health communications and address potential health crises proactively, ultimately benefiting both tourists and local communities.

The implications of our research extend into policy development, advocating for international cooperation to improve health infrastructure in tourism-dependent areas. The shortcomings of the IHR during the COVID-19 pandemic reveal a pressing need for reforms that strengthen

global health governance, particularly in vulnerable tourist destinations. Forming partnerships between governmental and private sectors can facilitate a coordinated response to health emergencies, ensuring effective crisis management.

Despite its contributions, our study acknowledges limitations. The model relies on historical data, which may not fully capture the evolving nature of health challenges or the diverse cultural contexts and local variations in infrastructure. Future research avenues include exploring interactions between health preparedness and other variables, such as economic and climate change metrics, and investigating how changing public perceptions of health risks influence tourism recovery strategies. Furthermore, leveraging advancements in data analytics and real-time monitoring could enhance the TALC model's resilience to unforeseen challenges.

In summary, this article advocates for a more integrated approach to tourism management, prioritising health preparedness as a foundational element of sustainable tourism development. By embedding health metrics into the TALC framework, stakeholders can develop resilient strategies capable of addressing the complexities posed by emerging health threats, thereby securing the future viability of the tourism industry. Involving all stakeholders and fostering strong partnerships between governmental and private entities will be crucial in ensuring effective crisis management and recovery (Okafor et al., 2021; Okafor et al., 2022; Sharma et al., 2021). Collaboration with healthcare systems remains paramount in this endeavour (Tasnim et al., 2023).

CRedit authorship contribution statement

M. Rodrigo: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization. **I. Ajala:** Writing – review & editing, Writing – original draft, Resources, Investigation. **A.K. Irhanida:**

Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Linear stability analysis

The classification of the equilibria of (3.6) follows from the analysis of the community matrix

$$J(T, I) = \begin{bmatrix} r(I) \left(1 - \frac{2T}{K}\right) & r'(I)T \left(1 - \frac{T}{K}\right) \\ -bI & a - bT \end{bmatrix}$$

and its eigenvalues, denoted by λ_1 and λ_2 .

The eigenvalues of

$$J(P_1) = \begin{bmatrix} r(0) & 0 \\ 0 & a \end{bmatrix}$$

are $\lambda_1 = r(0) < 0$ (see Eq. (3.3)) and $\lambda_2 = a > 0$. Therefore P_1 is an unstable saddle point.

The eigenvalues of

$$J(P_2) = \begin{bmatrix} -r(0) & 0 \\ 0 & a - bK \end{bmatrix}$$

are $\lambda_1 = -r(0) > 0$ (see Eq. (3.3)) and $\lambda_2 = a - bK$. If $K < \frac{a}{b}$, then $\lambda_2 > 0$ and P_2 is an unstable node. If $K > \frac{a}{b}$, then $\lambda_2 < 0$ and P_2 is an unstable saddle point.

The eigenvalues of

$$J(P_3) = \begin{bmatrix} 0 & r'(I^*) \frac{a}{b} \left(1 - \frac{a}{bK}\right) \\ -bI^* & 0 \end{bmatrix}$$

satisfy

$$\lambda^2 + aI^* r'(I^*) \left(1 - \frac{a}{bK}\right) = 0,$$

whose roots are

$$\lambda_1 = \left[aI^* r'(I^*) \left(\frac{a}{bK} - 1\right) \right]^{\frac{1}{2}}, \quad \lambda_2 = - \left[aI^* r'(I^*) \left(\frac{a}{bK} - 1\right) \right]^{\frac{1}{2}}.$$

If $K < \frac{a}{b}$, then $\lambda_1 > 0$ and $\lambda_2 < 0$, so P_3 is an unstable saddle point. If $K > \frac{a}{b}$, then $\lambda_{1,2}$ are pure imaginary and P_3 is a linear centre.

Appendix B. Derivation of the equation for the solution trajectories of (3.6)

The trajectories of (3.6) in the TI -plane satisfy

$$\frac{dT}{dI} = \frac{r(I)T \left(1 - \frac{T}{K}\right)}{I(a - bT)} \tag{B.1}$$

subject to the initial condition $T = T_0$ when $I = I_0$, with $I_0, T_0 > 0$. Define

$$R(I) = \int_{I_0}^I \frac{r(u)}{u} du. \tag{B.2}$$

Solving the separable Eq. (B.1) yields

$$\left[\frac{a}{T \left(1 - \frac{T}{K}\right)} + \frac{b}{\frac{T}{K} - 1} \right] dT = \frac{r(I)}{I} dI.$$

Decomposing into partial fractions, we get

$$\left(\frac{a}{T} + \frac{b - \frac{a}{K}}{\frac{T}{K} - 1}\right) dT = \left(\frac{a}{T} + \frac{bK - a}{T - K}\right) dT = \frac{r(I)}{I} dI.$$

If $(T_0, I_0) = (T(0), I(0))$ is any positive initial condition, then

$$\int_{T_0}^T \left(\frac{a}{u} + \frac{bK - a}{u - K}\right) du = R(I),$$

where $R(I)$ is as defined in Eq. (B.2). A straightforward integration gives

$$a \log\left(\frac{T}{T_0}\right) + (bK - a) \log\left(\frac{T - K}{T_0 - K}\right) = R(I),$$

which we can rewrite in implicit form as

$$|T|^a |T - K|^{bK - a} e^{-R(I)} = |T_0|^a |T_0 - K|^{bK - a}. \tag{B.3}$$

Appendix C. Approximation of the closed trajectories near P_3

Suppose that $K > \frac{a}{b}$. Near P_3 we see that $T < K$ and $T_0 < K$. Therefore Eq. (B.3) simplifies to

$$T^a (K - T)^{bK - a} e^{-R(I)} = T_0^a (K - T_0)^{bK - a}.$$

Making the substitutions $x(t) = T(t) - \frac{a}{b}$ and $y(t) = I(t) - I^*$, where $|x(t)| \ll 1$ and $|y(t)| \ll 1$, we obtain

$$\left[\frac{a}{b} \left(1 + \frac{bx}{a}\right)\right]^a \left[\frac{bK - a}{b} \left(1 - \frac{bx}{bK - a}\right)\right]^{bK - a} e^{-R(y + I^*)} = T_0^a (K - T_0)^{bK - a}.$$

An expansion about $y = I^*$ gives

$$R(y + I^*) \simeq R(I^*) + R'(I^*)y + \frac{1}{2}R''(I^*)y^2.$$

Eq. (B.2) implies

$$R'(I) = \frac{r(I)}{I}, \quad R''(I) = \frac{Ir'(I) - r(I)}{I^2},$$

so $R'(I^*) = 0$ and $R''(I^*) = \frac{r'(I^*)}{I^*}$ (see Eq. (3.3)). Taking logarithms, we deduce that

$$\begin{aligned} a \log\left(1 + \frac{bx}{a}\right) + (bK - a) \log\left(1 - \frac{bx}{bK - a}\right) - R(y + I^*) \\ = \log\left(T_0^a (K - T_0)^{bK - a}\right) - a \log\left(\frac{a}{b}\right) - (bK - a) \log\left(\frac{bK - a}{b}\right). \end{aligned}$$

Recalling that

$$\log(1 + z) \simeq z - \frac{z^2}{2}, \quad |z| \ll 1,$$

then

$$\begin{aligned} a \left(\frac{bx}{a} - \frac{b^2 x^2}{2a^2}\right) + (bK - a) \left[-\frac{bx}{bK - a} - \frac{b^2 x^2}{2(bK - a)^2}\right] - R(I^*) - \frac{r'(I^*)}{2I^*} y^2 \\ \simeq \log\left(T_0^a (K - T_0)^{bK - a}\right) - a \log\left(\frac{a}{b}\right) - (bK - a) \log\left(\frac{bK - a}{b}\right) \end{aligned}$$

or

$$\frac{b^3 K}{2a(bK - A)} x^2 + \frac{r'(I^*)}{2I^*} y^2 \simeq \log\left(\frac{\left(\frac{a}{b}\right)^a \left(\frac{bK - a}{b}\right)^{bK - a}}{T_0^a (K - T_0)^{bK - a}}\right) - R(I^*).$$

Finally,

$$\frac{b^3 K}{2a(bK - A)} \left(T - \frac{a}{b} \right)^2 + \frac{r(I^*)}{2I^*} (I - I^*)^2 \simeq \log \left(\frac{\left(\frac{a}{b} \right)^a \left(\frac{bK - a}{b} \right)^{bK - a} e^{-R(I^*)}}{T_0^a (K - T_0)^{bK - a}} \right).$$

This represents an ellipse, provided the right-hand side is positive, since $r'(I^*) > 0$ (see Eq. (3.3)) and $bK - a > 0$.

Appendix D. Parameter estimation formulas

For a suitable weighting function $w = w(t, s)$, where $t \in [t_i, t_f]$ and $s \in \mathbb{R}$, define the operator A by

$$(Ah)(s) = \int_{t_i}^{t_f} w(t, s)h(t) dt. \tag{D.1}$$

For example, if $w(t, s) = e^{-st}$, $t_i = 0$ and $t_f = \infty$, then Eq. (D.1) is the usual Laplace transform (finite Laplace transform if $t_f < \infty$). Differentiation of Eq. (D.1) with respect to s yields

$$(Ah)'(s) = \int_{t_i}^{t_f} D_2 w(t, s)h(t) dt, \tag{D.2}$$

where D_j denotes the partial derivative with respect to the j th variable. Then

$$\left(Ah \right)'(s) = w(t_f, s)h(t_f) - w(t_i, s)h(t_i) - \int_{t_i}^{t_f} D_1 w(t, s)h(t) dt \tag{D.3}$$

and

$$\left(Ah \right)'(s) = h(t_f) \frac{d}{ds} w(t_f, s) - h(t_i) \frac{d}{ds} w(t_i, s) - \int_{t_i}^{t_f} D_{12} w(t, s)h(t) dt. \tag{D.4}$$

Applying A to Eq. (4.3) and differentiating with respect to s , we deduce that

$$\begin{aligned} \left(Ah \right)'(s) &= c_1 (Ah_1)'(s) + c_2 (Ah_2)'(s), \\ \left(Ah \right)'(s) &= c_1 (Ah_1)'(s) + c_2 (Ah_2)'(s). \end{aligned} \tag{D.5}$$

All the s -dependent terms in Eq. (D.5) can be calculated for a given s since $h(t)$, $h_1(t)$ and $h_2(t)$ are assumed known for all $t \in [t_i, t_f]$. Choosing a convenient value $s = s_0$, we generate a 2×2 linear algebraic system Eq. (4.4) that is easily solved for the parameters c_1 and c_2 .

Appendix E. Average number of tourists and average growth rate

Assume that $K > \frac{a}{b}$ and consider a periodic solution of (3.6). Eq. (3.6b) becomes

$$\frac{I'(t)}{I(t)} = a - bT(t).$$

Integrating with respect to t from t_0 to $t_0 + P$, where t_0 is an arbitrary positive number, we get

$$\log \left(\frac{I(t_0 + P)}{I(t_0)} \right) = aP - b \int_{t_0}^{t_0 + P} T(t) dt.$$

But $I(t_0 + P) = I(t_0)$, hence

$$\frac{1}{P} \int_{t_0}^{t_0 + P} T(t) dt = \frac{a}{b}.$$

Eq. (3.6a) can be expressed as

$$\frac{T'(t)}{T(t) \left[1 - \frac{T(t)}{K} \right]} = \left[\frac{1}{T(t)} - \frac{1}{T(t) - K} \right] T'(t) = r(I(t)).$$

Integrating with respect to t from t_0 to $t_0 + P$ gives

$$\log \left(\frac{T(t_0 + P)}{T(t_0)} \right) - \log \left(\frac{|T(t_0 + P) - K|}{|T(t_0) - K|} \right) = \int_{t_0}^{t_0 + P} r(I(t)) dt.$$

As $T(t_0 + P) = T(t_0)$, we obtain

$$\int_{t_0}^{t_0 + P} r(I(t)) dt = 0.$$

References

- Adie, B. A., Amore, A., & Hall, C. M. (2022). Just because it seems impossible, doesn't mean we shouldn't at least try: The need for longitudinal perspectives on tourism partnerships and the SDGs. *Journal of Sustainable Tourism*, 30(10), 2282–2297.
- Bartolini, G. (2021). The failure of “core capacities” under the WHO international health regulations. *International and Comparative Law Quarterly*, 70(1), 233–250.
- Blinken, A. J., & Becerra, X. (2021). Strengthening global health security and reforming the international health regulations: Making the world safer from future pandemics. *Journal of the American Medical Association*, 326(13), 1255–1256.
- Boluk, K. A., Cavaliere, C. T., & Higgins-Desbiolles, F. (2019). A critical framework for interrogating the United Nations sustainable development goals 2030 agenda in tourism. *Journal of Sustainable Tourism*, 27(7), 847–864.
- Boluk, K. A., & Rasoolimanesh, S. M. (2022). Introduction to the special issue on “deepening our understandings of the roles and responsibilities of the tourism industry towards the United Nations sustainable development goals (SDGs)”. *Tourism Management Perspectives*, 41, Article 100944.
- Brauer, F., & Castillo-Chávez, C. (2012). *Mathematical models in population biology and epidemiology* (2nd ed.). New York: Springer.
- Broberg, M. (2020). A critical appraisal of the World Health Organization's international health regulations (2005) in times of pandemic: It is time for revision. *European Journal of Risk Regulation*, 11(2), 202–209.
- Burci, G. L. (2020). The legal response to pandemics: The strengths and weaknesses of the international health regulations. *Journal of International Humanitarian Legal Studies*, 11(2), 204–217.
- Butler, R. (Ed.). (2006a). *The tourism area life cycle vol 1: Applications and modifications*. Clevedon: Channel View Publications.
- Butler, R. (Ed.). (2006b). *The tourism area life cycle vol 2: Conceptual and theoretical issues*. Clevedon: Channel View Publications.
- Butler, R. (2022). COVID-19 and its potential impact on stages of tourist destination development. *Current Issues in Tourism*, 25(10), 1682–1695.
- Butler, R., & Dodds, R. (2022). Overcoming overtourism: A review of failure. *Tourism Review*, 77(1), 35–53.
- Caldera, A., Wickremasinghe, R., Newby, G., Perera, R., Mendis, K., & Fernando, D. (2023). Initial response to SARS-CoV-2 (COVID-19) outbreak in Sri Lanka: Views of public health specialists through an international health regulations lens. *PLoS One*, 18(11), Article e0293521.
- Cevik, S. (2022). Going viral: A gravity model of infectious diseases and tourism flows. *Open Economies Review*, 33(1), 141–156.
- Cockerham, G. (2022). The World Health Organization and COVID-19. Testing the international health regulations in a global pandemic. In J. M. Ryan (Ed.), *COVID-19: Cultural change and institutional adaptations*. London: Routledge.
- Czabanowska, K., & Kuhlmann, E. (2021). Public health competences through the lens of the COVID-19 pandemic: What matters for health workforce preparedness for global health emergencies. *The International Journal of Health Planning and Management*, 36(51), 14–19.
- Desai, K., Druyts, E., Yan, K., & Balijepalli, C. (2020). On pandemic preparedness: How well is the modeling community prepared for COVID-19? *Pharmacoeconomics*, 38(11), 1149–1151.
- Duro, J. A., Osório, A., & Perez-Laborda, A. (2023). Competition for domestic tourism in the COVID-19 pandemic: A characterization using a contest model. *Tourism Economics*, 29(2), 378–391.
- Farzanegan, M. R., Gholipour, H. F., Feizi, M., Nunkoo, R., & Andargoli, A. E. (2021). International tourism and outbreak of coronavirus (COVID-19): A cross-country analysis. *Journal of Travel Research*, 60(3), 687–692.
- Galvani, A., Lew, A. A., & Sotelo Perez, M. (2020). COVID-19 is expanding global consciousness and the sustainability of travel and tourism. *Tourism Geographies*, 22(3), 567–576.
- Gamboa-Maldonado, T., Marshak, H. H., Sinclair, R., Montgomery, S., & Dyjack, D. T. (2012). Building capacity for community disaster preparedness: A call for collaboration between public environmental health and emergency preparedness and response programs. *Journal of Environmental Health*, 75(2), 24–29.
- Gao, J., Shao, C., Chen, S., & Wei, Z. (2021). Evaluation of sustainable development of tourism cities based on SDGs and tourism competitiveness index: Analysis of 221 prefecture-level cities in China. *Sustainability*, 13, Article 12338.
- Garay, L., & Canoves, G. (2011). Life cycles, stages and tourism history: The Catalonia (Spain) experience. *Annals of Tourism Research*, 38(2), 651–671.
- Gössling, S., Scott, D., & Hall, C. M. (2021). Pandemics, tourism and global change: A rapid assessment of COVID-19. *Journal of Sustainable Tourism*, 29(1), 1–20.
- Hall, C. M. (2019). Constructing sustainable tourism development: The 2030 agenda and the managerial ecology of sustainable tourism. *Journal of Sustainable Tourism*, 27(7), 1044–1060.
- Hall, C. M., Scott, D., & Gössling, S. (2020). Pandemics, transformations and tourism: Be careful what you wish for. *Tourism Geographies*, 22(3), 577–598.
- Higgins-Desbiolles, F. (2021). The “war over tourism”: Challenges to sustainable tourism in the tourism academy after COVID-19. *Journal of Sustainable Tourism*, 29(4), 551–569.
- Hoarau, J. F. (2022). Is international tourism responsible for the outbreak of the COVID-19 pandemic? A cross-country analysis with a special focus on small islands. *Review of World Economics*, 158(2), 493–528.
- Holder, A. B., & Rodrigo, M. R. (2013). An integration-based method for estimating parameters in a system of differential equations. *Applied Mathematics and Computation*, 219(8), 9700–9708.
- Hovinen, G. R. (2002). Revisiting the destination lifecycle model. *Annals of Tourism Research*, 29(1), 209–230.
- IRTS (International Recommendations for Tourism Statistics). (2008). <https://www.unwto.org/tourism-statistics/on-basic-tourism-statistics-irts-2008> accessed 27 November 2024.
- Jones, T. (2012). A life cycle analysis of nature-based tourism policy in Japan. *Journal of the German Institute for Japanese Studies Tokyo*, 24(2), 179–211.
- Khan, Y., O'Sullivan, T., Brown, A., Tracey, S., Gibson, J., Généreux, M., ... Schwartz, B. (2018). Public health emergency preparedness: A framework to promote resilience. *BMC Public Health*, 18, 1344.
- Knowles, T., & Curtis, S. (1999). The market viability of European mass tourist destinations: A post-stagnation life-cycle analysis. *International Journal of Tourism Research*, 1(2), 87–96.
- Kraja, A., & Beshiri, X. (2019). Modeling of foreign tourists arrived by land and sea in Albania using logistic and Gompertz models. *Journal of Multidisciplinary Engineering Science and Technology*, 6(9), 10595–10599.
- Kruk, M. E. (2008). Emergency preparedness and public health systems lessons for developing countries. *American Journal of Preventive Medicine*, 34(6), 529–534.
- Lundtorp, S., & Wanhill, S. (2001). The resort lifecycle theory: Generating processes and estimation. *Annals of Tourism Research*, 28(4), 947–964.
- Marome, W., & Shaw, R. (2021). COVID-19 response in Thailand and its implications on future preparedness. *International Journal of Environmental Research and Public Health*, 18(3), 1089.
- Mertzanis, C., & Papastathopoulos, A. (2021). Epidemiological susceptibility risk and tourist flows around the world. *Annals of Tourism Research*, 86, Article 103095.
- Mihalic, T. (2020). Conceptualising overtourism: A sustainability approach. *Annals of Tourism Research*, 84, Article 103025.
- Namberger, P., Jackisch, S., Schmude, J., & Karl, M. (2019). Overcrowding, overtourism and local level disturbance: How much can Munich handle? *Tourism Planning & Development*, 16(4), 452–472.
- Nelson, C., Lurie, N., & Wasserman, J. (2007). Assessing public health emergency preparedness: Concepts, tools and challenges. *Annual Review of Public Health*, 28(1), 1–18.
- Novelli, M., Gussing Burgess, L., Jones, A., & Ritchie, B. W. (2018). No Ebola ... Still doomed – The Ebola-induced tourism crisis. *Annals of Tourism Research*, 70, 76–87.
- Okafor, L., Khalid, U., & Burzynska, K. (2021). Does the level of a country's resilience moderate the link between the tourism industry and the economic policy response to the COVID-19 pandemic? *Current Issues in Tourism*, 25(2), 303–318.
- Okafor, L. E., Khalid, U., & Gopalan, S. (2022). COVID-19 economic policy response, resilience and tourism recovery. *Annals of Tourism Research Empirical Insights*, 3(2), Article 100073.
- Oklevik, O., Gössling, S., Hall, C. M., Jacobsen, J. K. S., Grotte, I. P., & McCabe, S. (2019). Overtourism, optimisation and destination performance indicators: A case study of activities in fjord Norway. *Journal of Sustainable Tourism*, 27(12), 1804–1824.
- One Planet Network. (2024). **One Planet Vision for a responsible recovery of the tourism sector** accessed 9 January 2024. <https://www.oneplanetnetwork.org/knowledge-centre/resources/one-planet-vision-responsible-recovery-tourism-sector-covid-19>
- Özkan, B. I., & Boylu, Y. (2021). A study on the use of tourism as a soft power instrument in international relations. *Journal of Tourismology*, 7(1), 73–99.
- Petrevska, B., & Collins-Kreiner, N. (2017). A double life cycle: Determining tourism development in Macedonia. *Journal of Tourism and Cultural Change*, 15(4), 319–338.
- Petrović, D., Petrović, M., Bojković, N., & Cokić, V. P. (2020). An integrated view on country readiness and initial reaction to COVID-19: A study across European countries. *PLoS One*, 15(11), Article e0242838.
- Polyzos, S., Tsiotas, D., & Kantlis, A. (2013). Determining the tourism developmental dynamics of the Greek regions, by using TALC theory. *Tourism*, 8(2), 159–178.
- Rasoolimanesh, S. M., Ramakrishna, S., Hall, C. M., Esfandiar, K., & Seyfi, S. (2023). A systematic scoping review of sustainable tourism indicators in relation to the sustainable development goals. *Journal of Sustainable Tourism*, 31(7), 1497–1517.
- Razum, O., & Bozorgmehr, K. (2020). Global health needs more than international health regulations – The case of COVID-19. *Public Health Forum*, 28(3), 176–178.
- Rodrigo, M., Ajala, L., & Irhanida, A. K. (2023). Qualitative analysis of a tourism area life cycle model for interacting tourism destinations. *Annals of Tourism Research Empirical Insights*, 4(1), Article 100093.
- Roson, R., & van der Vorst, C. (2023). Assessing the economic and environmental consequences of the COVID-19 tourism collapse in Andalusia: What lessons can we draw for South-East Asian regions? *The Annals of Regional Science*, 71, 269–297.
- Roxas, F. M. Y., Rivera, J. P. R., & Gutierrez, E. L. M. (2022). Bootstrapping tourism post-COVID-19: A systems thinking approach. *Tourism and Hospitality Research*, 22(1), 86–101.
- Sharfstein, J. M., & Lurie, N. (2023). Public health emergency preparedness after COVID-19. *The Milbank Quarterly*, 101(S1), 653–673.
- Sharma, G. D., Thomas, A., & Paul, J. (2021). Reviving tourism industry post-COVID-19: A resilience-based framework. *Tourism Management Perspectives*, 37, Article 100786.
- Tasnim, Z., Shareef, M. A., Dwivedi, Y. K., Uma, K., Vinod, K., Tegwen, M. F., & Ramakrishnan, R. (2023). Tourism sustainability during COVID-19: Developing value chain resilience. *Operations Management Research*, 16, 391–407.
- UNDRR (United Nations Office for Disaster Risk Reduction). (2024). **What is the Sendai framework for disaster risk reduction?** accessed 26 April 2024 <https://www.undrr.org/implementing-sendai-framework/what-sendai-framework>.
- United Nations COVID-19 Global Humanitarian Response Plan (GHRP) COVID-19. (2020). **GHRP July update** accessed 26 April 2024 <https://reliefweb.int/report/world/global-humanitarian-response-plan-covid-19-april-december-2020-ghrp-july-up-date-enar>.
- UNWTO (United Nations World Tourism Organization). (2020). **'Sustainability as the new normal' a vision for the future of tourism [media release]**. UNWTO accessed 9 January 2024 <https://www.unwto.org/covid-19-oneplanet-responsible-recovery>.

- UNWTO (United Nations World Tourism Organization). (2024) accessed 27 November 2024 <https://www.unwto.org/tourism-statistics/key-tourism-statistics>.
- WHO (World Health Organization). (2023). International health regulations (IHR) core capacity index accessed 9 January 2024 [www.who.int/data/gho/data/themes/topics/indicator-groups/indicator-group-details/GHO/international-health-regulations-\(ihr\)-core-capacity-index](http://www.who.int/data/gho/data/themes/topics/indicator-groups/indicator-group-details/GHO/international-health-regulations-(ihr)-core-capacity-index).
- WHO (World Health Organization). (2024) accessed 27 November 2024 <https://apps.who.int/gho/data/view.main.UHC1HRV>.
- Wouters, O. J., Forman, R., Anderson, M., Mossialos, E., & McKee, M. (2023). The launch of the EU health emergency preparedness and response authority (HERA): Improving global pandemic preparedness. *Health Policy*, 133, Article 104844.
- Wut, T. M., Xu, J. B., & Wong, S. M. (2021). Crisis management research (1985–2020) in the hospitality and tourism industry: A review and research agenda. *Tourism Management*, 85(1), Article 104307.
- Yang, Y., Altschuler, B., Liang, Z., & Li, X. (2020). Monitoring the global COVID-19 impact on tourism. *Annals of Tourism Research*, 90, Article 103120.
- Zhou, S., Han, L., Liu, P., & Zheng, Z. J. (2020). Global health governance for travel health: Lessons learned from the coronavirus disease 2019 (COVID-19) outbreaks in large cruise ships. *Global Health Journal*, 4(4), 133–138.
- Zimmermann, K. F., Karabulut, G., Bilgin, M. H., & Doker, A. C. (2020). Inter-country distancing, globalisation and the coronavirus pandemic. *The World Economy*, 43(6), 1484–1498.
- Zulkarnaen, D., & Rodrigo, M. R. (2020). Modelling human carrying capacity as a function of food availability. *ANZIAM Journal*, 62(3), 318–333.

M. Rodrigo is an applied mathematician whose research interests include mathematical modelling, financial mathematics, mathematical biology and population ecology.

I. Ajala research interests include comparative politics, radicalisation, terrorism and diaspora politics, with a particular focus on Muslims in Europe.

A.K. Irhanida background is in town and country planning and specialises in alternative tourism with a focus on event tourism.