Satellite Imagery Reveals Differing Pathways to Adaptation to a Global Shock

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A large body of literature on adaptation strategies in social systems is based on the analysis of local-scale shocks in tightly coupled social-ecological systems. In this work, we identified and explored adaptation pathways at a global scale. We utilized nighttime lights (NTLs) satellite imagery, which are independent of national bias or misreporting, to assess impacts and recovery pathways from the COVID-19 shock. We categorized 170 countries into four different adaptation pathways: impacted and *Not Yet Recovered*, impacted and now *Back On Track*, impacted and *Built Back Better*,and *No Response* observed. We found that stringent lockdown policies were associated with a strong decline in nighttime lights. We also found that the immediate implementation of health policies at the onset of the pandemic, such as contact tracking and testing, was associated with faster NTL recovery and better overall adaptation, compared to countries whose response strategies were focused mainly on lockdown policies. These results provide a complement, not an alternative, to cross-country comparisons on adaptation to the COVID-19 pandemic using more traditional outcome measures such as infection rates, mortality, or GDP.

Adaptation | Nighttime lights | COVID-19 | Resilience

Constrained or enabled by local conditions and external influences, communities, institutions, and nations may take different actions in response to unexpected shocks, which in turn may influence the pathways to recovery (1). Each pathway, and their integration within portfolios of actions in response to the shock, is associated with certain benefits, impacts and risks, and may constrain or facilitate the ability to respond to other future shocks. Much of the literature on adaptation in social systems has tended to focus on local-scale shocks and communities that are intimately connected to, and largely dependent upon, natural systems such as farmers, herders, and fishers (2–4). In this work, we identify and explore global scale adaptation pathways to the COVID-19 pandemic shock, hopefully shedding light on how nations can adapt to future climate (5), health (6), economic (1, 7), social (8), and conflict (9) shocks .

The COVID-19 pandemic provides a unique opportunity to explore how nations were impacted by, responded to, and recovered from a near-global, near-simultaneous shock. However, cross-country comparisons of adaptation strategies to the COVID-19 pandemic are impaired by the lack of homogeneous information, as data on infection rates, hospitalizations, mortality, and economic activity were not collected in a consistent manner across countries (10) and, in some cases, severely under-reported, when not deliberately manipulated (11). For example, compare and contrast epidemiological data from two neighboring countries, Tanzania and Kenya. Tanzania (whose late president, John Magufuli, was an outspoken COVID-19 skeptic) has a slightly larger population than Kenya (66 vs 54 millions, respectively) but reported eighth times fewer COVID-19 cases (42,906 vs 342,937) and nearly seven times fewer deaths (846 vs 5,688) than Kenya in spite of similar population densities, economies, climatic conditions and Global Health Security Index (12). Likewise, the US state of California, home to ca. 39 million inhabitants, reported more total deaths from COVID-19 than the People's Republic of China with a population of 1.4 billion. Statistics on economic activity, such as GDP, are also susceptible to misreporting bias (13–15) and are typically only available on an annual time-scale (16).

To overcome the limitations of conventional data to understand the impact of COVID-19, we used satellite imagery of nighttime lights (NTLs) to quantify and categorize country-level responses and recovery pathways. NTL data are independently measured, are available at a fine temporal scale, and are known to be correlated with on-the-ground human activity (both across space and time). NTLs are often used as a proxy for economic activity: for instance, (17) developed a

Significance Statement

Using statistics reported by national governments to study global events can be limited if data reporting standards vary widely across countries. To overcome reporting biases, our study uses satellite images of nighttime lights to measure changes in brightness over time in response to the COVID-19 pandemic, a recent near-global near-simultaneous shock. Adaptation responses to the shock vary, but most countries can be broadly categorized into one of four adaptation pathways based on the severity of the initial response and the speed of recovery. This same approach can be used to study adaptation to other shocks when high resolution data on mortality or economic activity is not available at a global scale.

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statistical framework to use NTLs to estimate income growth at the national and sub-national level and (18) found that the correlation between NTLs and economic activity in Sweden is strong enough to make it a good proxy for population and establishment density. In a more recent example, (14) shows that NTLs are strongly correlated with on-the-ground economic activity and this relationship can be used to prove that autocracies, on average, overstate yearly GDP growth by 35%. (19) found a significant relationship between a nighttime lights-based inequality indicator and existing estimates of net income inequality; this correlation between light-based and traditional income estimates exists not only across countries, but also on a smaller spatial scale comparing the 50 states within the United States.

A number of studies have used NTL to investigate single large-scale events such as natural disasters or civil unrest. For example, the curfew imposed by the Egyptian government on Cairo neighborhoods in response to terrorist attacks and widespread protests led to a drop in NTLs in late-2016 and early-2017 (20, 21). Nighttime lights have been used to measure the impacts of events ranging from Hurricanes Katrina (22) and Maria (23) to earthquakes in Nepal and Chile (24).

Here we found that the COVID-19 pandemic also had a dramatic affect on NTLs in many parts of the world, akin to a major natural disaster or armed conflict. As a preview of our main results, we show in Figure 1 that a drop in NTLs was clearly detectable in a selection of large cities such as Tokyo, Los Angeles, and Cairo. Each panel in the figure shows the change in NTL from the same quarter in the previous year. In the second quarter of 2020 (April-June), Cairo, LA, and Tokyo are noticeably darker compared to the same time period in 2019. In fact, we find that the majority of countries experienced a dramatic impact on human activity during the COVID-19 pandemic that was visible from space. 77% of countries (approx. 86% of the world's population) experienced a reduction in NTLs during the pandemic unlike anything else they experienced during the period 2014-2019 (Figure S1).

Here, we used country-level NTLs and regression techniques to calculate measures of impact and recovery for 170 countries. Specifically, for each country we used pre-pandemic NTL data to project NTL trajectories as if the pandemic had never happened. The projected trends in NTLs were then used as baseline to identify different adaptation pathways to the COVID-19 pandemic. We then explored correlational relationships between the drop in NTLs and strategic policy responses across geographical regions and income levels.

Other studies have used NTLs to gauge the impacts of the pandemic and consistently observed reductions in NTL luminosity during pandemic periods (25–35). However, our study is the first global-level cross-country comparison contextualizing NTL patterns within the framework of adaptation and resiliency, i.e., the stringency of lockdown policies and the extent of testing, tracing, and vaccination.

We found that high-income and most European countries experienced the largest immediate reductions in NTLs whereas low-income and many African countries showed the smallest immediate responses. We also found that the immediate reduction in NTLs across regions and income groups was best explained by the stringency of lockdown policies. On the contrary, health-related policy measures, such as increased testing and contact tracing, were significantly correlated with smaller negative impacts over the long-term.

Results

We first fit a Weighted Least Squares regression model (Equation 1 in Materials and Methods section) to quarterly NTL values for each country individually, while accounting for cloud cover, satellite sensor re-calibrations in Q1 2017 (36), quarterly seasonal effects, and changes in post-pandemic trends. Then, we estimated counterfactual values by removing the pandemic effects on NTL trends from Equation 1. The resulting counterfactual values are essentially a continuation of pre-pandemic trends estimated using Equation 2. Figure 2 illustrates how we fit our regression model and calculate impacts for the country of Kenya. In Panel (a), the solid line represents the fitted values estimated by Equation 1. The dashed line represents the projected counterfactual values estimated using Equation 2. We classified countries as fully recovered from the pandemic when their NTL trends returned in line with their counterfactual values, i.e., with the pre-pandemic trend line projected as if the pandemic had never happened. Kenya, for instance, took 10 quarters to fully recover (Quarter 3 of 2022).

We calculated the country level magnitude of the pandemic impact as the difference between observed values and projected counterfactual values, i.e., the distance between the blue points and the dashed line in Figure 2 (b). The red error bars indicate negative values and the blue error bars indicate non-negative values. We calculated three simple measures that summarize response and recovery pathways: immediate impact, first-year impact, and overall impact between the onset of the pandemic and the third quarter in 2023. *Immediate impact* is estimated by the coefficient β_{1i} in equation 1 and is depicted by the purple double-arrow line in Figure 2 (a) and (b), *first-year impact* is the cumulative, net impact in NTLs for all four quarters in 2020 (i.e. the net sum of the first four error bars in Figure 2 (b) starting at t=0), and *overall impact* is the cumulative net impact on NTLs from Q1 2020 to Q3 2023 (i.e., the net sum of all the error bars in Figure 2 (b) starting at t=0). This process was repeated for each country separately (see *Materials and Methods*) for more details).

Categorizing Impact, Adaptation, and Recovery Pathways.

We categorize countries using the criteria summarized in Table 1. *No Response* countries (n=38) like Greece, El Salvador, the Solomon Islands, Iran, and Ghana had non-negative values for both immediate and first-year impact. Affected countries (n=132) are countries that experienced a negative impact immediately (Quarter 1 of 2020) or were net negative at the end of 2020. We further classify affected countries into two groups: recovered (n=97) and not yet recovered (n=35). If a country's fitted trend line never crosses over their projected counterfactual trend line up to Quarter 3 of 2023, then they have *not yet recovered.* Some countries that have not yet recovered include Nigeria, the Philippines, Qatar, and Portugal. Countries that *recovered* (e.g. France, Brazil, Egypt, Cameroon, and South Korea) had their fitted trend line cross over the projected counterfactual trend line at some point during the time series. We further classify

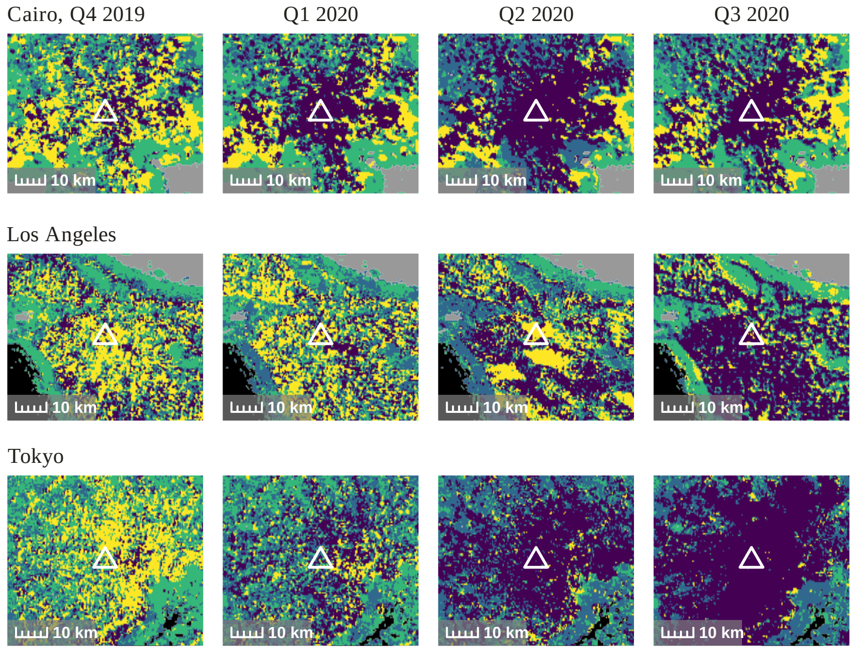

Fig. 1. This figure shows impacts on nighttime lights in select cities. Darker colors (purple and blue) indicate darkening relative to the same quarter in the previous year. Lighter colors (green and yellow) indicate brightening relative to the same quarter in the previous year.

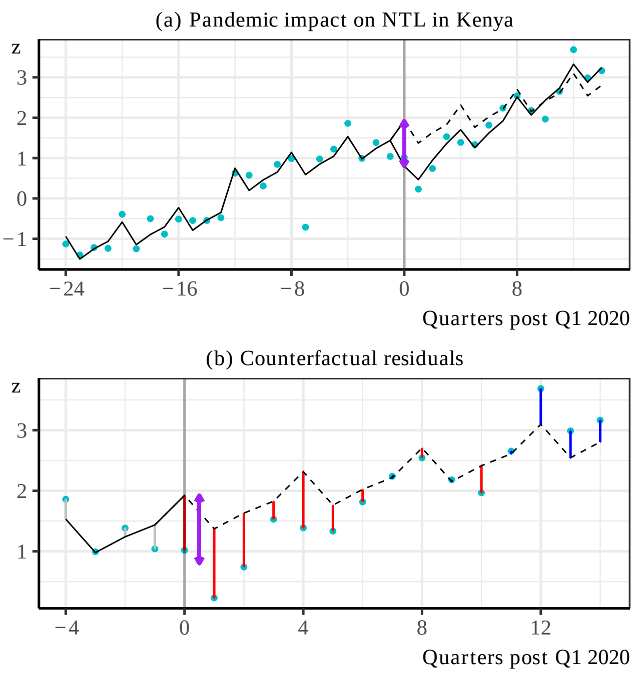

Fig. 2. An example of how impacts are calculated for Kenya. Blue points are the observed values from the NTL data. The solid line shows the fitted values estimated by equation 1. The dashed line shows the counterfactual values estimated by equation 2, i.e., the projected NTL trend as if the COVID-19 pandemic never occurred. Purple lines are the estimated *immediate impact* in the first quarter of the pandemic estimated by 1. Red error bars indicate negative impacts and the blue error bars indicate non-negative impacts on NTLs. Quarter 2 in 2018 was an obvious outlier for Kenya, likely due to heavy flooding that displaced nearly 300,000 people (this also explains why Kenya is one of a small number of countries to have previously experienced an NTL shock larger than the pandemic shock).

recovered countries into two groups: back on track (n=38) and built back better (n=59). Countries that were *back on track* returned to their counterfactual (i.e., their projected pre-pandemic trend), but had a net negative overall impact. Countries like Fiji, Uruguay, Russia, Egypt, and Japan were back on track as of Quarter 3 of 2023. Countries that *built back better* were initially impacted by the pandemic but, by the end of 2023, they had bounced back *above* the counterfactual, i.e., their projected pre-pandemic trend. These countries include Peru, Iraq, Germany, Mexico, and the Gambia.

Figure 3 shows both pre-pandemic and post-pandemic deviations from trend (error bars shown in Figure 2 Panel (b)) over time for all countries in each category. Post-pandemic impacts start in Quarter 1 2020 (t=0) and are calculated as residuals from the projected counterfactual values. We see that No Response countries, like Turkmenistan, tend to exceed their projected counterfactual trend. The autocratic government of Turkmenistan largely denied the existence of COVID-19 within its borders and did not implement large-scale mobility or health-related measures (37).

Compared to No Response countries (Figure 3a, left panel), the impact trajectories of affected countries are noisier. The United States (Figure 3a, right panel) exhibits sustained prolonged negative impacts, perhaps due to the fact that decentralized pandemic responses varied widely across US states (38). Malaysia had not yet recovered back to their projected counterfactual NTL trend by the end of 2023 (Figure 3b, left panel). Compared to the USA, the Malaysian government responded as a centralised authority with the declaration of a Movement Control Order (MOC) (39). This lockdown approach was successful at "flattening the curve" but this was also a time of political instability. The government and prime minister changed

Table 1. Definitions used to categorize countries into No Response, Recovered, or Not Yet Recovered. The entire time series spans 3 years, or 12 quarters

Category	Definition
No Response	No impacts (immediate impact ≥ 0 **and** first-year impact ≥ 0)
Affected	Negative impacts (immediate impact < 0 **or** first-year impact < 0)
	Affected
Not yet recovered	Fitted values $<$ projected counterfactual values for the entire time series
Recovered	At least one fitted value $\geq$ projected counterfactual value
	Recovered
Back on track	Overall impact < 0
Built back better	Overall impact ≥ 0

three times in less than 2 years during a time when the government had "unprecedented economic power" (40). The prime minister who led Malaysia during the peak of the pandemic has subsequently been charged with bribery and money laundering through the government's COVID fund (41). Both Argentina and Egypt appear to recover and get back on track, possibly due to an early and decisive response. Argentina's approach included a concerted effort between federal and local governments to administer lockdown policies and public information campaigns (42). Egypt's economy is one of the few that reported positive economic growth in 2020, possibly due to its extreme but comparatively brief lockdown policy and robust economic interventions (43). India had a slight darkening in 2020 but managed to build back better surpassing its projected counterfactual trend for much of the time series. This is consistent with the "miraculous" containment of the virus early on in the pandemic (44). India was hit especially hard during a second-wave in 2021 but managed to roll-out a massive vaccination drive to bolster recovery (44).

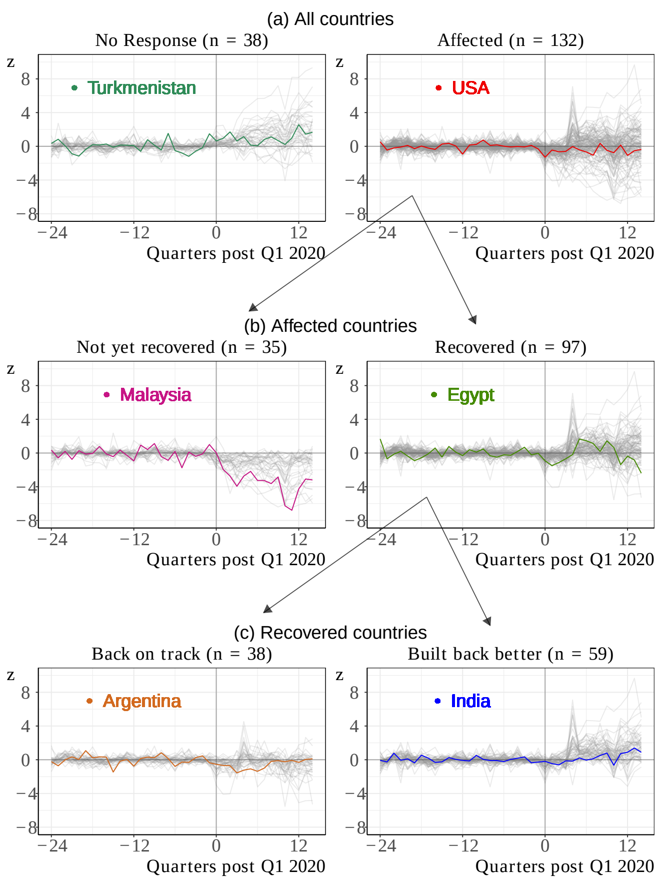

Fig. 3. Quarterly residuals (i.e., the error bars in figure 2 (b)) on the y-axis and time on the x-axis. In the pre-pandemic period (left of the vertical line at t = 0), a value of zero on the y-axis means that the observed value is equal to the fitted value for that quarter. In the post-pandemic period (right of the vertical line at t = 0), a value of zero on the y-axis means that the observed value is equal to the projected counterfactual value. A country was considered impacted by the pandemic if its NTLs dropped below the projected counterfactual at the onset of the pandemic (right panel a). Impacted countries might have not recovered back to the projected counterfactual by the end of the pandemic (left panel b). Those that recovered (right panel b), either went back in line with pre-pandemic projections (left panel c), or even exceed them (right panel c).

Most of the countries Affected and Recovered groups experienced a significant brightening in the early quarters of 2021 supporting the idea that pent-up economic demand started to offset the initial negative economic impacts of 2020 (45). Many of the countries in the Affected group also seemed to experience another darkening between 2021 and 2022, possibly due to additional waves of infections following viral mutations. While most of the countries that recovered are categorized as Built Back Better, roughly one-third of all countries are Back on Track but have not fully offset the impact of the pandemic. A full list of countries and their adaptation pathway category are provided in Table S1.

Policy responses and impact measures. We used country level variation in our three measures of impact and recovery (i.e., *Immediate*, *First-year*, and *Overall* impact) to explore the relationships between adaptation responses and outcomes across geographical regions and levels of economic development. Our baseline estimates were derived by regressing the three impact measures on categorical variables for income level and geographic region, separately. We then sequentially added controls for types of policy response (i.e., lockdown *vs.* health-related) to investigate how accounting for policy response might affect the baseline estimates. We used the lockdown Stringency Index and of the Containment and Health Index by Oxford COVID-19 Government Response Tracker (46) to summarize the intensity of lockdown and national health policies, which are

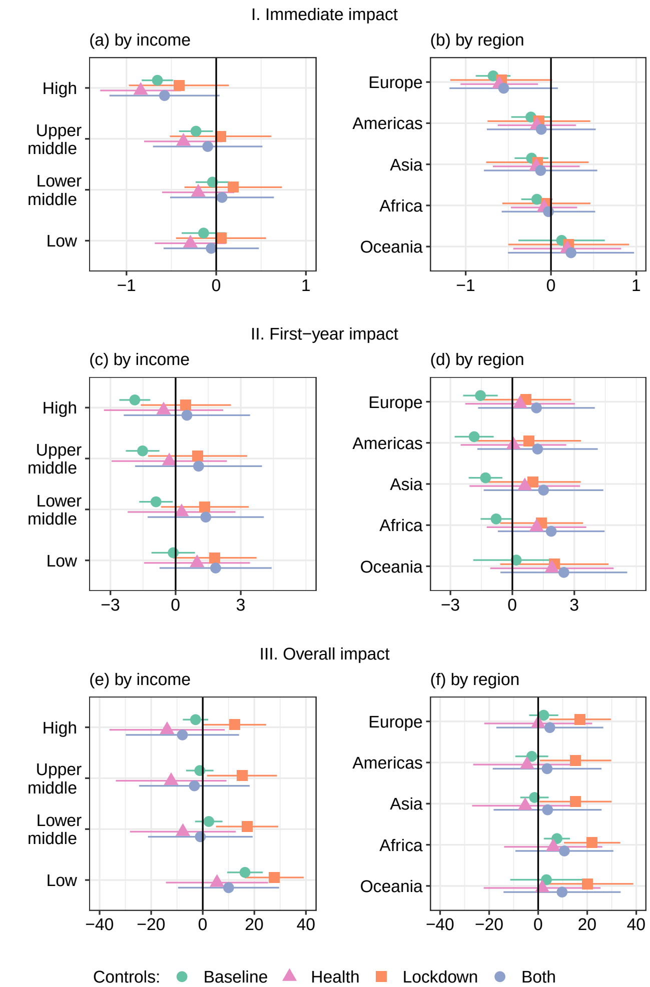

Fig. 4. Coefficients estimated using Equation 1. The outcome variables (immediate, first-year, overall) are our estimated country-level impacts. Baseline estimates control for World Bank income group in panel (a), geographical region in panel (b), and do not include any additional controls. Adaptation controls (health and lockdown) control for intensity of each policy type and are derived from indices sourced from OxGRT (46). Policies are averages of daily values for the relevant policy period. For immediate impact, this period is Q1 2020. For first-year impact, the period is Q1 2020 - Q4 2020. For overall impact, the period is Q1 2021 - Q2 2021.

available as daily values. We calculated averages of these daily values over the appropriate time periods for each of the three impact measures (Figure 4).

We found that high and upper-middle income countries exhibited the largest immediate NTL drop (see Baseline coefficients), equivalent to 0.5 standard deviations from the pre-pandemic mean NTL level (4a). In other words, NTLs in high income countries were immediately impacted by the pandemic more than lower income countries. The negative impact in the high income group was mostly driven by European countries (4b). Therefore, high-income, mostly European countries exhibited the largest decreases in luminosity at the beginning of the pandemic.

When controlling for the stringency of lockdown policies in the first Quarter of 2020, the immediate impact for high-income countries was not statistically significant from zero at the 95% confidence level (Figure 4 Panel (a)). This suggests that the large NTL response observed in high-income countries during this quarter was associated with more stringent lockdown policies. The same pattern holds for Upper middle income countries, also suggesting that the observed reduction in nighttime lights is explained by the stringency of lockdown policies in Quarter 1 of 2020. As an alternative to Figure 4, Table S2 presents regression results where we control for income level (or region), lockdown, and health-related policies. We observe weak evidence that lockdowns are correlated with a reduction in NTL whereas health policies are correlated with an increase in NTL (during the first quarter of 2020).

First-year impacts ((c) and (d)) seem to be more widespread than immediate impacts (note the change in scale on the horizontal axis, measured as cumulative net standard deviations from pre-pandemic means). The baseline estimates for the income group regressions show that countries in high, upper-middle, and lower-middle income groups all exhibited significant negative impacts during the first year of the pandemic. Thus, for the majority of countries, the COVID-19 pandemic is associated with large-scale changes in human behavior that are observable from space. Again, high-income countries had the largest reductions with quarterly luminosity being roughly 1.6 standard deviations lower than the projected counterfactual, on average. Regional estimates show that countries in the Americas have slightly larger negative impacts than other regions. However, controlling for the intensity of response turns all first-year impact estimates positive across income groups and geographical regions. This is additional evidence that much of the drop in NTLs during 2020 was driven by lockdown policies. This negative correlation between lockdown stringency and NTL impacts in the first year of the pandemic is further supported by results from fixed effects regressions presented in Table S3.

Overall impacts (up to Quarter 3 of 2023) highlight different effects for different adaptation responses. Baseline estimates suggest that low-income countries had non-negative overall impacts, mostly driven by countries in Africa. In other words, NTL luminosity in these countries was unaffected by the pandemic. When we control for the stringency of lockdown policy, overall impacts turn positive in all regressions. However, when we control for the intensity of health-related policy (i.e., contact tracing, testing, and vaccination), overall impacts become slightly more negative. This suggests that countries with more stringent lockdowns during 2021 are associated with larger NTL reductions (less economic activity) and countries with more health-focused policy responses during 2021 are associated with minimal reductions in NTL (sustained economic activity).

This finding is echoed in Figure 5. This figure shows average overall impacts for countries falling above and below average levels of policy intensity. We see that countries with above average lockdown intensity tend to have larger reductions in NTL. In general, countries with more muted policy responses seem to have maintained or increased luminosity during the pandemic. The exception is countries that had (i) health policies above average intensity and (ii) lockdowns below average intensity. These countries exhibit the largest NTL growth over this period, suggesting that their economies continued to grow as would have been expected (or exceeded expectations). Overall, these results suggest

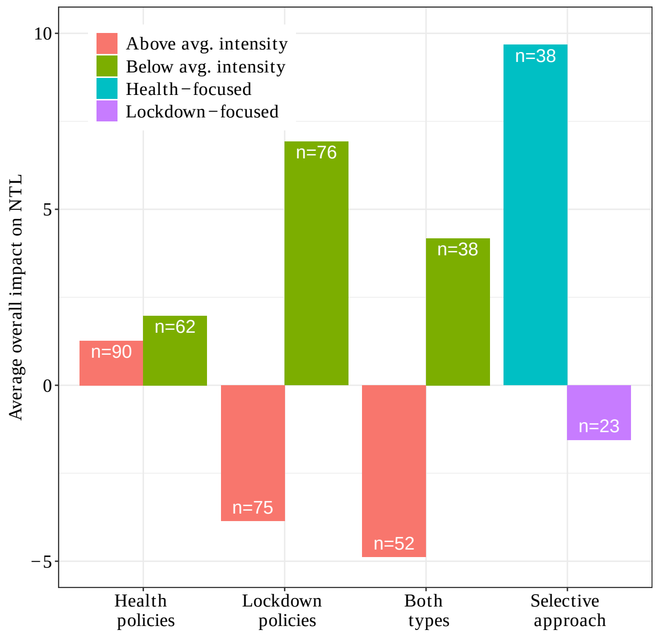

Fig. 5. Overall impacts for countries falling above or below the average policy intensity for a certain type or mix of adaptation responses. The x-axis shows the specific policy type or combination. *Both* considers the average overall impact of countries with both policies above or below the average intensity for that policy. *Selective* shows the average overall impact when one policy type was above the average intensity and the other policy type was below the average intensity, e.g. Health-focused means above average health policy intensity combined with below average lockdown policy intensity.

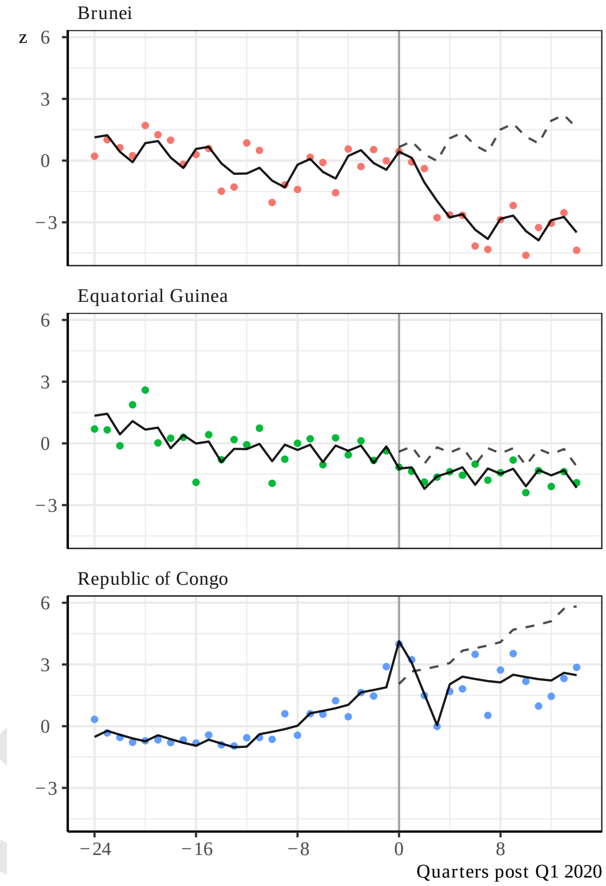

Fig. 6. Quarterly nighttime lights for three different countries: Brunei, Equatorial Guinea, Republic of Congo (actual NTL data shown as points with fitted trend line in black, projected counterfactual trend post Q1 2020 is shown as a dashed line). According to national GDP statistics, all three countries reported positive economic growth from 2020-2023,

that countries that prioritized health-related policies over lockdown adapted to the pandemic better than countries that prioritized lockdown over health-related policies. These interpretations are supported by results from fixed effects regressions presented in Table S3. Additional results that also explore the use of economic support policies and official reports of infection rates are shown in Figure S2. There are no obvious patterns across income groups or geographical regions.

Comparison to GDP-based Categories. How do our results compare to those that would be obtained using national GDP statistics? Here we highlight countries that were "unaffected" by the pandemic if we use our methodology and nationally-reported GDP statistics but "affected" if we use NTLs: Belarus, Benin, Brunei, Burundi, Egypt, Equatorial Guinea, Republic of Congo, and Sierra Leone. Note that these are countries classified as authoritarian or "Not Free" by Freedom House. In Figure 6, we show three examples of how these countries appear to have been negatively impacted in terms of NTL.

Discussion and Conclusion

This study shows that 77% of countries experienced a significant darkening during the first year of the COVID-19 pandemic. Of those countries that exhibit a NTL response, 73% recovered to their counterfactual trend by Quarter 3 of 2023. Out of the countries that recovered, 60% fully recovered all the luminosity "lost" during the pandemic. The variation in lockdown policies explains much of the reduction in luminosity experienced across income groups and geographic regions. These findings are consistent with a separate study exploring the effect of lockdown policies on luminosity in large cities (34). That study focuses on the four weeks before and after a lockdown and we show that this effect persists when we expand the spatial scale and time horizon. Increased focus on health-related policies (i.e., contact tracing and testing) as an adaptation response seems to have a converse relationship with nighttime lights, allowing the lights to "stay on" with lower overall impacts.

There are, of course, caveats and limitations in using nighttime lights to infer responses to and recovery from any event, including the COVID-19 pandemic. The use of artificial light at night is not a perfect indicator of on-the-ground economic activity: businesses might close down but keep their lights on, conversely, less activity at night might be offset by increased economic activity during the day. In spite of these limitations, our study shows that large-scale changes in human behavior occurred during the COVID-19 pandemic were detectable from space by tracking NTLs. Our findings also suggest that both existing adaptive capacity and real-time decision-making mattered. High income countries had more capacity to implement large-scale responses like country-wide lockdown. But, even within lower-income nations, policy responses appeared to mitigate the economic impacts of the pandemic. Across income groups, strict health measures combined with less stringent mobility controls appeared to minimize the economic impacts of the pandemic. Therefore, a lack of adaptive capacity can be offset by well-informed policy-making.

Materials and Methods

Nighttime lights. Nighttime lights data come from the monthly cloud-free composites collected by the NASA/NOAA Suomi National Polar-orbiting Partnership (SNPP) Visible Infrared Imaging Radiometer Suite (VIIRS) day-night band (DNB) and processed by the Earth Observation Group (EOG), based at the Colorado School of Mines in the USA. The monthly composites are averaged nightly pixel values that are free of sunlight, moonlight, and clouds (47). The EOG also provides annual masks which zero out noisy background pixels and pixels with low luminosity values (47). We apply the 2021 EOG V.2 mask to all months from 2021 to 2023 because the EOG does not yet provide V.2 masks after 2021. Furthermore, the data we use has undergone a correction for stray-light which allows for more data coverage toward the poles by extrapolating the pixels most affected by stray-light (48). After this initial processing, we sum the monthly values across all pixels within each country to calculate country-level total monthly luminosity. Then, we average the monthly values for each quarter to obtain quarterly NTL values.

Counterfactual trend, impacts, and recovery. We fit a linear regression to quarterly NTL while accounting for satellite sensor calibrations in Q1 2017 (36), seasonality in NTL levels, and potential pandemic impacts. Our goal was to quantify the immediate, first-year, and overall impacts on NTL luminosity during the pandemic. Equation 1 shows our main regression model. All regressions included quarter-of-year fixed effects to account for seasonality (coefficient λ_q) and weights for the average number of cloud-free days in each quarter. Therefore, we put less weight on quarters with more cloudy days. We used a dummy variable *pre*2017, set to 1 for all quarters before the year 2017 (the year of the sensor recalibration). We included the interaction between this dummy variable and time trend t to control for sensor calibrations in Q1 2017 (α_{2i}) and allow for this calibration to change the underlying linear time trend (α_{3i}). The dummy variable *covid* was set to 1 for all quarters in 2020 and allowed us to estimate the pandemic's initial shock (β_{1i}). We included the interaction between this dummy variable with the time trend t to estimate the change in the linear time trend during the first year of the pandemic (β_{2i}). The dummy variable *vaccine* was set to 1 for all quarters after the introduction of vaccines (2021 and onward). We used this dummy to estimate immediate (γ_{1i}) and changes in the linear (γ_{2i}) time trend after the development of the vaccine starting in Q1 2021.

The counterfactual values $\hat{y}^c_{ti}$ were estimated by removing the pandemic effects $\hat{\beta}_{1i}$, $\hat{\beta}_{2i}$, $\hat{\gamma}_{1i}$, and $\hat{\gamma}_{2i}$ estimated by equation 1. This left only the long-term linear time trend $\hat{\alpha}_{1i}$, and seasonal effects $\hat{\lambda}_q$, while controlling for sensor calibration effects beginning in 2017 ($\hat{\alpha}_{2i}$ and $\hat{\alpha}_{3i}$). Equation 2 shows how we estimated the counterfactual values using the parameters $\hat{\alpha}_{1i}$, $\hat{\alpha}_{2i}$, $\hat{\alpha}_{3i}$, and $\hat{\lambda}_q$ from Equation 1.

Impacts were then calculated as follows. *Immediate impact* for country i was estimated by the coefficient β_{1i} in equation 1, in other words, the change in intercept due to the onset of the pandemic. *First-year impact* was the sum of the *impacts* ($\hat{y}^c_{ti} - y_{ti}$) for the four quarters of 2020. *Overall impact* was the sum of the *impacts* ($\hat{y}^c_{ti} - y_{ti}$) from Q1 2020 to Q3 2023. See Figure 2 for a more visual explanation of these calculations.

Policy responses and impact measures. We investigated how country-level policy responses correlate with variation in impacts across geographical regions and income groups. First, we estimate Equation 3 for World Bank income groups and Equation 4 for geographical regions. The outcome variable Y_i is one of three

$$\begin{aligned} y_{ti} = \alpha_{1i}\mathrm{t} \,+\, \alpha_{2i}\,\mathrm{recalibration}_t \,+\, \alpha_{3i}\,(\mathrm{recalibration}_t \times \mathrm{t}) \\ +\,\beta_{1i}\,\mathrm{covid}_t \,+\, \beta_{2i}\,(\mathrm{covid}_t \times \mathrm{t}) \\ +\,\gamma_{1i}\,\mathrm{vaccine}_t \,+\, \gamma_{2i}\,(\mathrm{vaccine}_t \times \mathrm{t}) \,+\, \lambda_q \,+\, \epsilon_{ti} \end{aligned} \quad [1]$$

$$\hat{y}^c_{ti} = \hat{\alpha}_{1i}\mathrm{t} \,+\, \hat{\alpha}_{2i}\,\mathrm{pre2017}_t \,+\, \hat{\alpha}_{3i}\,(\mathrm{pre2017}_t \times \mathrm{t}) \,+\, \hat{\lambda}_q \quad [2]$$

country-level impact measures defined in the previous section that capture income and recovery of NTLs (*immediate*, *first-year*, and *overall*). The estimated coefficients give us the average country-level impact on NTLs within each income group and geographical location. These serve as our baseline estimates. Then, we sequentially add controls for policy responses (*health* and *lockdown*) to see how they change the baseline estimates. All policy response indices are the average daily value during the relevant "policy" time period. For *immediate impact*, the relevant policy period is the first quarter of 2020. For *first-year impact*, the relevant policy period is the entire year of 2020. For *overall impact*, the policy period is 2021 since many countries had returned to normalcy by 2022. Our policy variables come from the Oxford COVID-19 Government Response Tracker (OxGRT) which provides information on pandemic response measures (46). They use this information to construct indices with larger values indicating larger responses. Lockdown stringency is provided directly by OxGRT which they refer to as the stringency index. The health policy index is constructed using OxGRT methods and data(46).

$$\begin{aligned} \mathrm{Y}_i = \delta_1\mathrm{high}_i \,+\, \delta_2\,\text{upper-middle}_i \,+ \\ \delta_3\,\text{lower-middle}_i \,+\, \delta_4\,\mathrm{low}_i \,+\, \mu_i \end{aligned} \quad [3]$$

$$\begin{aligned} \mathrm{Y}_i = \theta_1\mathrm{Europe}_i \,+\, \theta_2\,\mathrm{Americas}_i \,+ \\ \theta_3\,\mathrm{Asia}_i \,+\, \theta_4\,\mathrm{Africa}_i \,+\, \theta_4\,\mathrm{Oceania}_i \,+\, \upsilon_i \end{aligned} \quad [4]$$

GDP Comparisons. We measured impacts on annual GDP using the same technique we used for quarterly NTL. Because there is a lag in the release of national GDP statistics, we restrict the sample period to run from 2014 to 2021. Note that when we compare results obtained using annual GDP to those obtained using quarterly NTL we also restrict the quarterly NTL dataset to the time period 2014-2021.

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1. P Johnstone, J Schot, Shocks, institutional change, and sustainability transitions. *Proc. Natl. Acad. Sci.* **120**, e2206226120 (2023).
2. JE Cinner, et al., Sixteen years of social and ecological dynamics reveal challenges and opportunities for adaptive management in sustaining the commons. *Proc. Natl. Acad. Sci.* **116**, 26474–26483 (2019).
3. M Casari, C Tagliapietra, Group size in social-ecological systems. *Proc. Natl. Acad. Sci.* **115**, 2728–2733 (2018).
4. K Findlater, R Kozak, S Hagerman, Difficult climate-adaptive decisions in forests as complex social–ecological systems. *Proc. Natl. Acad. Sci.* **119**, e2108326119 (2022).
5. A Taberna, T Filatova, A Hadjimichael, B Noll, Uncertainty in boundedly rational household adaptation to environmental shocks. *Proc. Natl. Acad. Sci.* **120**, e2215675120 (2023).
6. C Chen, DP Goldman, J Zissimopoulos, JW Rowe, RN on an Aging Society, Multidimensional comparison of countries' adaptation to societal aging. *Proc. Natl. Acad. Sci.* **115**, 9169–9174 (2018).
7. M Coronese, F Lamperti, K Keller, F Chiaromonte, A Roventini, Evidence for sharp increase in the economic damages of extreme natural disasters. *Proc. Natl. Acad. Sci.* **116**, 21450–21455 (2019).
8. MR Ramos, MR Bennett, DS Massey, M Hewstone, Humans adapt to social diversity over time. *Proc. Natl. Acad. Sci.* **116**, 12244–12249 (2019).
9. CF Schleussner, JF Donges, RV Donner, HJ Schellnhuber, Armed-conflict risks enhanced by climate-related disasters in ethnically fractionalized countries. *Proc. Natl. Acad. Sci.* **113**, 9216–9221 (2016).
10. H Lau, et al., Evaluating the massive underreporting and undertesting of covid-19 cases in multiple global epicenters. *Pulmonology* **27**, 110–115 (2021).
11. A Karlinsky, D Kobak, Tracking excess mortality across countries during the covid-19 pandemic with the world mortality dataset. *elife* **10**, e69336 (2021).
12. EE Cameron, JA Bell, JB Nuzzo, Global health security index: Building collective action and accountability. *Glob. Heal. Secur. Index* (2019).
13. A Marx, MZ Rogers, Analysis of panamanian dmsp/ols nightlights corroborates suspicions of inaccurate fiscal data: A natural experiment examining the accuracy of gdp data. *Remote. Sens. Appl. Soc. Environ.* **8**, 99–104 (2017).
14. LR Martinez, How much should we trust the dictator's gdp growth estimates? *J. Polit. Econ.* **130**, 2731–2769 (2022).
15. A Briviba, B Frey, L Moser, S Bieri, Governments manipulate official statistics: Institutions matter. *Eur. J. Polit. Econ.* **82**, 102523 (2024).
16. G Chi, H Fang, S Chatterjee, JE Blumenstock, Microestimates of wealth for all low-and middle-income countries. *Proc. Natl. Acad. Sci.* **119**, e2113658119 (2022).
17. JV Henderson, A Storeygard, DN Weil, Measuring economic growth from outer space. *Am. economic review* **102**, 994–1028 (2012).
18. C Mellander, J Lobo, K Stolarick, Z Matheson, Night-time light data: A good proxy measure for economic activity? *PloS one* **10**, e0139779 (2015).
19. MU Mirza, C Xu, Bv Bavel, EH Van Nes, M Scheffer, Global inequality remotely sensed. *Proc. Natl. Acad. Sci.* **118**, e1919913118 (2021).
20. Egypt: Fearing protests, police arrest hundreds. *Hum. Rights Watch.* (2016).
21. K Deasy, Egypt: Curfew imposed after violent cairo protest. *The World from PRX* (2016).
22. Y Qiang, Q Huang, J Xu, Observing community resilience from space: Using nighttime lights to model economic disturbance and recovery pattern in natural disaster. *Sustain. Cities Soc.* **57**, 102115 (2020).
23. MO Román, et al., Satellite-based assessment of electricity restoration efforts in puerto rico after hurricane maria. *PloS one* **14**, e0218883 (2019).
24. X Fan, et al., Rapid detection of earthquake damage areas using viirs nearly constant contrast night-time light data. *Int. J. Remote. Sens.* **40**, 2386–2409 (2019).
25. CD Elvidge, T Ghosh, FC Hsu, M Zhizhin, M Bazilian, The dimming of lights in china during the covid-19 pandemic. *Remote. Sens.* **12**, 2851 (2020).
26. RC Beyer, S Franco-Bedoya, V Galdo, Examining the economic impact of covid-19 in india through daily electricity consumption and nighttime light intensity. *World Dev.* **140**, 105287 (2021).
27. N Dasgupta, Using satellite images of nighttime lights to predict the economic impact of covid-19 in india. *Adv. Space Res.* **70**, 863–879 (2022).
28. M Alahmadi, et al., Using daily nighttime lights to monitor spatiotemporal patterns of human lifestyle under covid-19: The case of saudi arabia. *Remote. Sens.* **13**, 4633 (2021).
29. M Roberts, Tracking economic activity in response to the covid-19 crisis using nighttime lights–the case of morocco. *Dev. Eng.* **6**, 100067 (2021).
30. K Shi, Y Cui, S Wu, S Liu, The impact of covid-19 pandemic on socioeconomic activity exchanges in the himalayan region: A satellite nighttime light perspective. *IEEE Geosci. Remote. Sens. Lett.* (2023).
31. EC Stokes, MO Román, Tracking covid-19 urban activity changes in the middle east from nighttime lights. *Sci. reports* **12**, 8096 (2022).
32. RC Beyer, T Jain, S Sinha, Lights out? covid-19 containment policies and economic activity. *J. Asian Econ.* **85**, 101589 (2023).
33. Y Zhang, N Peng, S Yang, P Jia, Associations between nighttime light and covid-19 incidence and mortality in the united states. *Int. J. Appl. Earth Obs. Geoinformation* **112**, 102855 (2022).
34. G Xu, T Xiu, X Li, X Liang, L Jiao, Lockdown induced night-time light dynamics during the covid-19 epidemic in global megacities. *Int. J. Appl. Earth Obs. Geoinformation* **102**, 102421 (2021).
35. AM Khan, H Park, M Roberts, PS Wibisana, , et al., When the lights go out: The economic impacts of covid-19 on cities globally, (The World Bank), Technical report (2022).
36. RC Beyer, Y Hu, J Yao, *Measuring quarterly economic growth from outer space.* (International Monetary Fund), (2022).
37. HT Hashim, AEA El Rassoul, J Bchara, A Ahmadi, DE Lucero-Prisno III, Covid-19 denial in turkmenistan veiling the real situation. *Arch. Public Heal.* **80**, 8 (2022).
38. S Bergquist, T Otten, N Sarich, Covid-19 pandemic in the united states. *Heal. policy technology* **9**, 623–638 (2020).
39. A Tayeb, PH Hong, Malaysia: Improvised pandemic policies and democratic regression. *Covid-19 Asia: Law policy contexts* pp. 321–334 (2021).
40. CM Tee, WY Wong, CW Hooy, Government power and the value of political connections: Evidence from covid-19 economic lockdowns. *Finance Res. Lett.* **47**, 102706 (2022).
41. F Mao, J Head, Muhyiddin yassin: Ex-malaysia pm charged with corruption over covid spending. *BBC News* (2023) Accessed: 2024-05-23.
42. PJ Garcia, et al., Covid-19 response in latin america. *The Am. journal tropical medicine hygiene* **103**, 1765 (2020).
43. MA Abdel-Moneim, R Rizk, Egypt and the response to the covid-19 pandemic. *Good public governance a global pandemic* **479**, 479–487 (2020).
44. SD Sharma, India's fight against the covid-19 pandemic: lessons and the way forward. *India Q.* **78**, 9–27 (2022).
45. T Walmsley, A Rose, D Wei, The impacts of the coronavirus on the economy of the united states. *Econ. disasters climate change* **5**, 1–52 (2021).
46. T Hale, et al., A global panel database of pandemic policies (Oxford COVID-19 Government Response Tracker). *Nat. Hum. Behav.* (2021).
47. CD Elvidge, M Zhizhin, T Ghosh, FC Hsu, J Taneja, Annual time series of global viirs nighttime lights derived from monthly averages: 2012 to 2019. *Remote. Sens.* **13**, 922 (2021).
48. S Mills, S Weiss, C Liang, Viirs day/night band (dnb) stray light characterization and correction in *Earth observing systems XVIII.* (SPIE), Vol. 8866, pp. 549–566 (2013).