

Systems Analysis and Decision Making for Resilience of Energy Systems

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Abstract—Decision making for resilient infrastructure systems requires methods for assessing risk across political, social, economic, and physical domains. Traditional risk assessments for physical systems often consider only historical data in prioritization and decision making. This paper presents a systems and risk analysis framework to identify resource threats to energy system development priorities. The methods are demonstrated for the case of alternative energy investments in Turkmenistan. Twenty-seven sub-basins are ordered according to three satellite-observed metrics representing energy generation potential. Disruptions to the baseline system order, induced by 30-year forward-looking projection scenarios, are used to identify the most and least resilient sub-basins in the context of energy system development.

Keywords—risk assessment, resilience, decision analysis, multicriteria analysis, alternative energy, systems evaluation

I. INTRODUCTION AND BACKGROUND

Central Asia, comprising Kazakhstan, Kyrgyzstan, Tajikistan, Turkmenistan, and Uzbekistan, faces considerable threats to its long-term resilience, as evidenced by the region's disproportionate rises in temperatures compared to global averages [1], [2]. The vulnerability of fossil fuel-driven economies and scarcity of shared water resources in the region threaten to increase tensions [2]. Many of the Central Asian countries, including Turkmenistan, have declared ambitious strategies for long-term resilience, but continued reliance on fossil fuels to achieve economic goals will hinder progress towards these adaptation targets [2], [3]. Turkmenistan announced their National Climate Change Strategy in 2012 (revised in 2019) and submitted a Nationally Determined Contribution to the Paris Agreement outlining a 20% reduction of greenhouse gas emissions by 2030, relative to 2010 emissions levels [4], [5]. Turkmenistan also officially signed on to the Global Methane Pledge in late 2023, agreeing to contribute to the global collective effort to reduce worldwide methane emissions by at least 30% from 2020 to 2030 [4], [6]. However,

the country's hydrocarbon-focused economy presents challenges to achieving these adaptation targets.

Turkmenistan is a country of 5.7 million people and a desert-dominated 469,930 km² land area [7]. The country's economy is heavily focused in natural gas and oil extraction and export. Its gas reserves rank fourth globally, accounting for approximately 10% of total global reserves [8]. As of 2022, natural gas accounted for 89% of Turkmenistan's domestic energy production (with oil comprising the other 11%) and 100% of its electricity generation [9]. The economy is quite energy intensive, driven in large part by natural gas seepage from oil and gas exploration [10]. Domestic energy consumption per GDP was the highest in the world in 2023 [11]. Turkmenistan is the fourth largest energy exporter in Eurasia and 31st largest globally, with energy exports having increased by nearly 50% since the year 2000 [9]. Similarly, electricity exports have increased more than ten-fold since 2000, increasing most dramatically since 2020 [9]. These energy exports fund most domestic infrastructure projects in other sectors such as transportation [12]. However, a reliance on fossil fuel-based energy export leaves the Turkmen economy vulnerable to energy price shocks, the global shift away from fossil fuels, carbon taxes, etc.

Alternative energy sources such as solar and wind have become some of the most affordable sources of electricity in many regions, representing an opportunity for energy and electricity sector infrastructure development that can further support Turkmenistan in achieving its energy resilience goals [9]. Approximately 80% of Turkmenistan's land is desert, providing the potential landscape for solar photovoltaic (PV) and wind energy infrastructure [10]. Solar PV, in particular, shows great potential in the country due to the more than 300 sunny days annually [3]. However, as of 2021, alternative energy sources accounted for less than 0.1% of energy consumption in Turkmenistan [9]. Turkmen policies, such as the National Strategy for the Development of Renewable Energy

II. METHODS

A. Data Collection and Analysis

until 2030 (adopted in 2020) and the Law of Turkmenistan On Renewable Energy Sources (adopted in 2021), have outlined general goals for small scale renewable energy generation in remote regions by 2020 and larger scale generation infrastructure by 2030, however no quantitative targets appear to have been set [5], [10]. Realizing the potential of these alternative energy sources will require attention to the resilience of supply chains for key hardware and electronic components. Ensuring timely and affordable access to technologies such as solar panels, wind turbines, and control systems is critical for scaling infrastructure deployment. As the Central Asian region continues to face evolving natural conditions, regional weather extremes, and potential for supply chain disruption, ensuring that decision-making tools are risk-informed will be critical for building a resilient energy and economic future.

In recent years, several studies have considered alternative energy potential for Turkmenistan and other Central Asian countries. Laldjebaev, Isaev, and Saukhimov [13] provided an overview of the potential and current state of alternative energy development in Central Asia. The authors estimate substantial solar resources available in Turkmenistan (655,000 MW) and 10,000 MW of wind energy potential. Satymov, Bogdanov, and Breyer [14] simulated several scenarios of a potential renewable energy transition in Turkmenistan, using linear optimization to minimize costs while meeting energy demands. The study found that Turkmenistan could achieve a 100% renewable energy scenario by 2050 at minimum cost, and found that regardless of the rate of transition, a 100% renewable energy system would achieve reduced cost relative to fossil fuel reliance. Notably, this study uses only historical data to map the solar and wind resources of the country. Bahrami, Teimourian, Okoye, and Khosravi [15] assessed the wind energy potential of Turkmenistan by studying the hourly wind speed data of a typical meteorological year at eighteen potential sites. They found Kazandzhi, Dashoguz, Gyzylarbat, and Turkmenbashi to hold the best potential for wind energy, and further analyzed specific turbine models. Abylkasymova et al. [16] surveyed the national policies supporting alternative energy development in the region, noting that Turkmenistan, as of 2019, had little to no regulatory policy or fiscal incentives supporting this development.

This paper describes a systems analysis and decision-aid model for energy system investment priorities of Turkmenistan. We assess the system as a set of 27 system components – hydrological sub-basins of Turkmenistan – against three system order metrics which serve as proxies for energy generation potential – surface downwelling radiation, wind speed, and maximum air temperature. Sub-basins are prioritized across three scenarios – a baseline (as-is), an alternative energy development scenario, and a fossil-fueled development scenario. Crucially, the approach extends the current literature by considering both historical observations of natural conditions and long-term future projections. The results provide an ordering of the system components based on energy generation potential for each scenario, highlighting the importance of incorporating projections of evolving natural conditions into decision-making for resilient systems.

This study utilizes the HydroBASINS dataset to subdivide Turkmenistan and its border regions into 27 sub-basins (Fig. 1). This dataset, from the World Wildlife Fund, provides boundaries of sub-basins worldwide at twelve hierarchical levels of resolution [17]. For this work, the Level 05 (L05) HydroBASINS were selected to ensure adequate data coverage while maintaining a high level of resolution. This study prioritizes amongst the L05 basins wholly or partially within Turkmenistan using historical and forward-looking projections of energy resource metrics.

Whereas other studies, e.g., [14], [15], have considered only historical data in their assessment of Turkmenistan's alternative energy potential, this study assesses both recent historical observations as well as forward-looking projections of long-term uncertainty. The projections in this work were collected from the Coupled Model Intercomparison Project Phase 6 (CMIP6), a global collaboration to compare and assess General Circulation Models (GCMs) of historic, present, and future conditions [18], [19]. A notable component of CMIP6 is consideration of Shared Socio-economic Pathways (SSPs). These SSPs provide realistic scenarios of future conditions given the presence, or absence, of human mitigation and adaptation strategies. The SSPs vary from highly successful mitigation strategies (SSP 1), representing reduced energy intensity, to unsuccessful mitigation strategies (SSP 5), representing high dependence on fossil fuels for development into the future [20].

The projections used in this study were sourced from NASA's NEX-GDDP-CMIP6. This dataset downscales CMIP6 to a high spatial resolution of 0.25 x 0.25 degrees, sufficient to assess energy resource conditions at the L05 HydroBASINS resolution [21]. The downscaled data set also provides further bias correction of the GCMs by using historical data to improve regional model performance and best account for local topographical features and finer-scale gradients, both critical to our local-level analysis. Historical data from 2000-2023 and future projections for 2025-2055 were collected. Annual averages of daily observations for near-surface air temperature

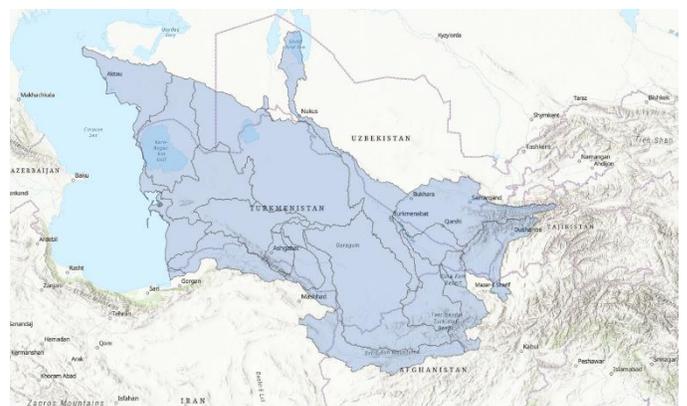


Fig. 1. Twenty-seven sub-basins of the study area, comprising the energy system for resilience assessment (generated in ArcGIS)

(mean, minimum, and maximum, in degrees Celsius), downwelling shortwave radiation (W/m^2), and wind speed (m/s) were spatially averaged for each L05 basin. To provide the most representative view of each basin and avoid single-year outliers, the average of the most recent five-year period (2019-2023) was recorded for the baseline analysis of historical data. For future scenarios, the average of the 2051-2055 projections were recorded to reflect a 30-year outlook.

B. Systems and Risk Analysis for Resilient Systems

This work adapts methods of previous work introducing scenario-based multi-criteria preferences models of system risk and resilience [22], [23], [24], [25]. The model is centered on three input sets: system components, system order metrics, and scenarios. The set of system components, $X = \{x_1, x_2, \dots, x_n\}$, is the set of alternatives that a decision-maker would like to prioritize amongst. In this case, the system components are the 27 sub-basins of Turkmenistan and its border regions. In general, system components can be locations, infrastructure assets, technologies, or policies. A set of system order metrics, $M = m_1, m_2, \dots, m_p$, is defined as the criteria by which the system components will be assessed to establish an ordering of system components. In this case, the system order metrics are chosen as proxy measures of energy generation potential—downwelling shortwave radiation as a proxy for solar PV potential [26], [27], wind speed as a proxy for wind turbine energy potential [28], and maximum air temperature as a proxy for heat-induced solar PV inefficiency [29], [30], [31]. Finally, the set of scenarios, $S = \{s_1, s_2, \dots, s_q\}$, represents critical or strategically important potential future states that could be disruptive to the system itself and/or to stakeholder priorities. In this case, the two scenarios studied are SSPs as defined by CMIP6 (Table I). In general scenarios may include natural disasters, economic stress, political changes, technological innovations, and more.

After defining the system components, system metrics, and scenarios, a baseline system order is established by assessing each sub-basin's baseline energy generation potential. First, each system metric is assigned a weight, w_{j_b} , reflecting its relative importance to energy resilience in the baseline scenario: high ($w_{j_b} = 4$), medium ($w_{j_b} = 2$), low ($w_{j_b} = 1$), or none ($w_{j_b} = 0$) (Table II). Next, the most recent five years of historical data are collected and averaged for each metric. The five-year averages for each metric are normalized on a 0-1 scale, with the highest value amongst the set indexing at 1.0 and the lowest value at 0.0 (note that for maximum air temperature, where higher values indicate a negative property for energy generation potential, this formula is reversed such that the lowest value indexes at 1.0 and the highest value indexes at 0.0). This normalization provides a relative measure by which to assess features of energy potential across the study area, offering a comparison of alternative energy suitability. Numerical scores, $(x_{ij})_b$, are assigned to each sub-basin/metric pair as follows: sub-basins indexing between 0.76-1.0 receive a score of 3, sub-basins indexing between 0.51-0.75 receive a score of 2, sub-basins indexing between 0.26-0.50 receive a score of 1, and sub-basins indexing below 0.26 receive a score of 0. An overall score for each system component in the baseline scenario, $V(x_i)_b$, is

TABLE I. SCENARIOS FOR RISK-INFORMED DECISION MAKING FOR ENERGY SYSTEM PRIORITIES

Index	Scenario	Description
s.01	SSP 126	Global shift towards lowering consumption and energy intensity with alternative energy production [20]
s.02	SSP 585	Economic development is driven by hydrocarbons and energy intensive lifestyles [20]

TABLE II. SYSTEM ORDER METRICS AND IMPORTANCE WEIGHTS FOR ENERGY SYSTEM ANALYSIS

System Order Metric	Baseline	s.01 – SSP 126	s.02 – SSP 585
Downwelling shortwave radiation (W/m^2)	Low ($w_{j_b} = 1$)	High ($w_{j_1} = 4$)	Low ($w_{j_2} = 1$)
Wind speed (m/s)	Low ($w_{j_b} = 1$)	High ($w_{j_1} = 4$)	Low ($w_{j_2} = 1$)
Maximum air temperature (Celsius)	None ($w_{j_b} = 0$)	Medium ($w_{j_1} = 2$)	Medium ($w_{j_2} = 2$)

calculated as a weighted sum of the metric weights, $(w_j)_b$, and sub-basin/metric scores, $(x_{ij})_b$, as in (1).

$$V(x_i)_b = \sum_{j=1}^p (w_j)_b (x_{ij})_b, \forall i \in \{1, 2, \dots, n\} \quad (1)$$

The baseline system order is established by sorting the system components in decreasing order (with ties) of their overall baseline score.

The above process is then repeated for each of the scenarios in S . System order metrics are assigned scenario-specific weights, w_{j_k} , to reflect the differences in values that occur in different scenarios. For example, wind speed is given a high weight in the *s.01 – SSP 126* scenario, where wind can serve an important role in maintaining energy system resilience. The sub-basin/metric pairs are scored using the same indexing methodology as described above, but using forward-looking projections instead of historical observations. These projections are sourced from the CMIP6 models, and are specific to each scenario. To project long-term futures for infrastructure planning and decision-making, a 30-year time horizon is chosen and the projections reflect the 2051-2055 projected annual averages. The five-year average projections were chosen to limit the effects of any particular outlier year in the dataset. Scenario-specific scores, $V(x_i)_k$, are calculated for each sub-basin as the weighted sum in (2), where $(w_j)_k$ is the weight of system order metric m_j in scenario s_k and $(x_{ij})_k$ is the sub-basin/metric score in scenario s_k .

$$V(x_i)_k = \sum_{j=1}^p (w_j)_k (x_{ij})_k, \forall i \in \{1, 2, \dots, n\} \quad (2)$$

Unique system orders are established for each scenario by sorting the sub-basin scores in decreasing order for each scenario.

We then define a measure of disruptiveness for each scenario, calculated as the sum of squared differences as in (3), where $R(x_i)_b$ is the system order position, or rank, of initiative x_i in the baseline scenario and $R(x_i)_k$ is the system order position, or rank, of initiative x_i in the scenario s_k .

$$D(s_k) = \sum_{i=1}^n (R(x_i)_b - R(x_i)_k)^2 \quad (3)$$

The disruptiveness measure is then normalized on a 0-100 scale for ease of comparison.

III. RESULTS

The system order and scenario disruption results are summarized in Fig. 2, Fig. 3, and Fig. 4. Fig. 2 shows the sub-basins arranged from top to bottom according to their rank in the baseline scenario, represented by the black bar in each row. The red bar represents how far a sub-basin falls in the system order under the SSP scenarios. Likewise, the blue bar represents how far a sub-basin rises in the system order under the SSP scenarios.

Two of the sub-basins tied for first in the baseline system order, $x_{.25}$ - *L05 Basin: 4050531200* and $x_{.19}$ - *L05 Basin: 4050274280*, are along the eastern border of Turkmenistan, crossing into Uzbekistan to the east and Afghanistan to the south. These sub-basins have high solar and wind energy generation potential when considering historical observations of downwelling shortwave radiation and wind speed. However, these sub-basins, along with the other sub-basin tied for first in the baseline system order, the more centrally-located $x_{.13}$ - *L05 Basin: 2050671440*, fall to near the bottom of the system order for scenario $s_{.02}$ - *SSP 585*. This fall is primarily attributed to their relatively low projected wind speeds under this scenario, representing a decrease in wind energy generation potential. In fact, under this scenario each of these three sub-basins is projected to experience decreases in average wind speed of 16-36% by 2055. On the other hand, the five sub-basins ranked lowest in the baseline scenario, $x_{.01}$ - *L05 Basin: 2050065970*, $x_{.02}$ - *L05 Basin: 2050066030*, $x_{.26}$ - *L05 Basin: 4050531330*, $x_{.27}$ - *L05 Basin: 4050538040*, and $x_{.21}$ - *L05 Basin: 4050484700*, all rise into the top 10 in system order for scenario $s_{.02}$ - *SSP 585*. These sub-basins are projected to experience increases in both wind speed and downwelling shortwave radiation by 2055, while not experiencing the extreme high

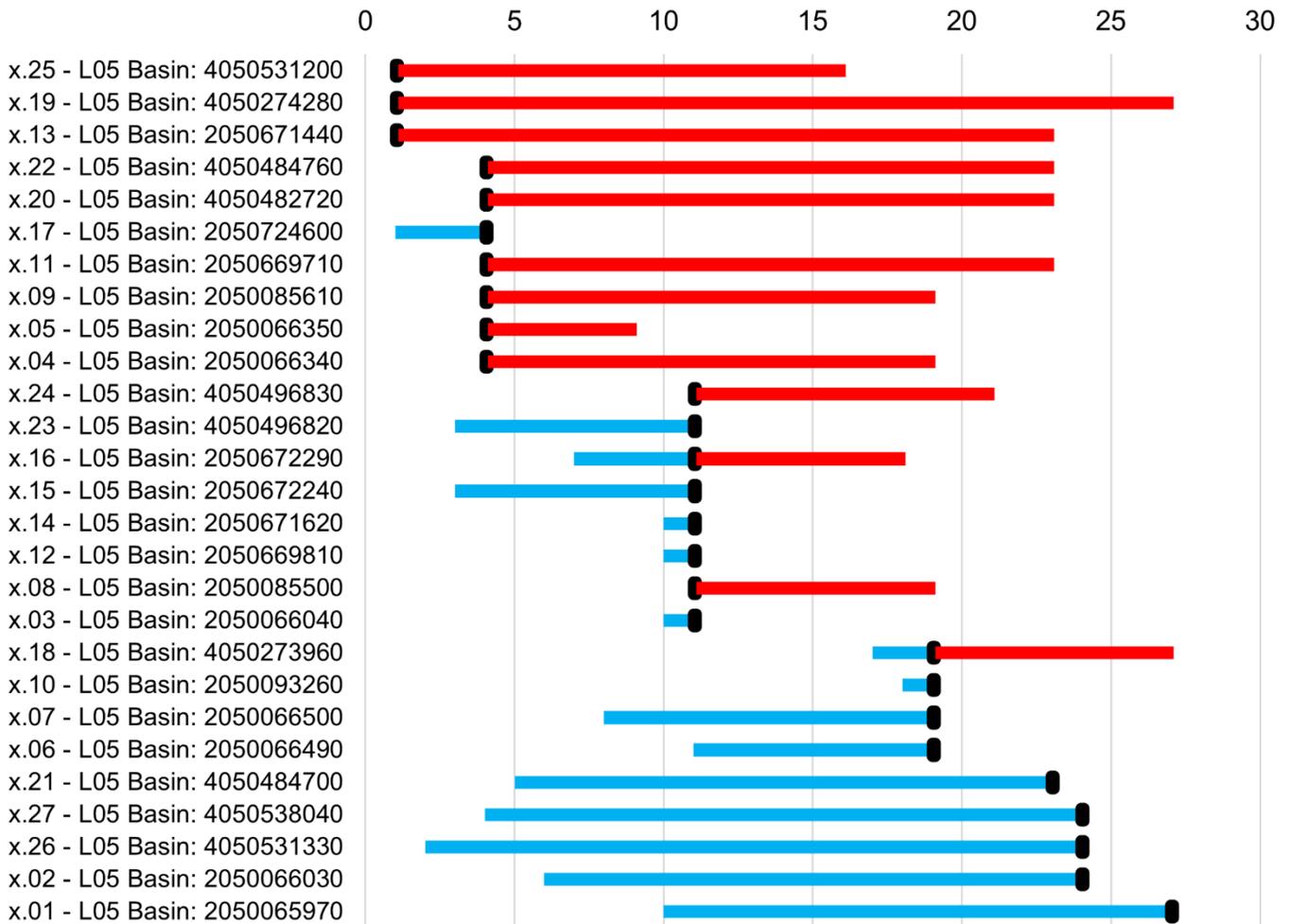


Fig. 2. Disruption of energy system priorities by long-term development scenarios, where red indicates fall in system order and blue indicates rise in system order (relative to baseline)

temperatures that may lead to inefficient solar generation in other sub-basins in the region. One of the largest sub-basins by land area in the study area, *x.09 - L05 Basin: 2050085610* which covers northeast Turkmenistan, is ranked very highly in the baseline (tied for fourth). However, this sub-basin falls to 18th position in *s.01 - SSP 126* and 19th position in *s.02 - SSP 585* due to the projected decreases in wind speed for both scenarios. Sub-basins located along the coast of the Caspian Sea in western Turkmenistan, such as *x.03 - L05 Basin: 2050066040* and *x.05 - L05 Basin: 2050066350*, generally remain ranked in the top 10 due to the higher wind speeds observed and projected relative to other sub-basins in the study area. Notably, *x.17 - L05 Basin: 2050724600*, is consistently positioned in the top four of the system order in the baseline (tied in fourth position) and both future risk scenarios (first position in both scenarios). This sub-basin is located in the southwest of Turkmenistan, with the majority of the sub-basin's land area falling in Iran and Afghanistan. While the land area within Turkmenistan is smaller, this sub-basin represents the most optimal energy resource features, given the future projections for 2055, for longer term energy generation.

Fig. 3 presents the shifts in system order for each scenario in map form, with sub-basins shaded red falling in system order and sub-basins in blue rising in system order. Most of the sub-basins within the study area experience a similar shift (i.e., rise or fall) in both scenarios, as evidenced by the similarity of Fig. 3a and Fig. 3b. Notably, sub-basins in central Turkmenistan generally fall in system order position when taking into account their long-term future projections. Sub-basins along the Caspian coast and in southern and eastern Turkmenistan generally become more viable options for energy generation when considering their forward-looking projections. These sub-basins, which may not have been high priorities for energy investment given only historical data become higher priorities when considering projected resource variability in the region.

Fig. 4 displays the normalized scenario disruptiveness measures for the two scenarios analyzed. These results indicate significant volatility in system order between the baseline scenario and the *s.01 - SSP 126* and *s.02 - SSP 585* scenarios. Interestingly, the system orders for the two SSP scenarios are generally similar, with twenty-one of the sub-basins being ranked within ± 5 positions between scenarios. However, the system orders established in both SSP scenarios vary greatly from the baseline scenario. This result highlights how the projected future volatility in downwelling shortwave radiation, wind speed, and maximum air temperature will considerably disrupt the current rankings of sub-basins with the greatest solar PV and wind energy potential. Decision-making based solely on recent historical observations of these metrics would not consider this volatility and would result in vastly different system priorities system priorities and projected outcomes than if future scenarios were considered.

IV. DISCUSSION AND CONCLUSIONS

This paper introduces methods for integrating historical observations and future projections of climatological metrics into a systems analysis and decision aid for alternative energy systems. Sub-basins are prioritized considering only historical observations, and subsequently reprioritized for a 30-year

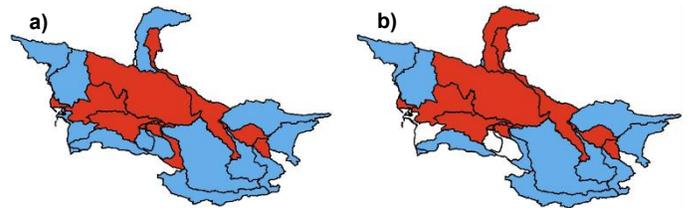


Fig. 3. Resilience of energy system components for (a) *s.01 - SSP 126* and (b) *s.02 - SSP 585*, where red indicates fall in system order and blue indicates rise in system order (relative to baseline)

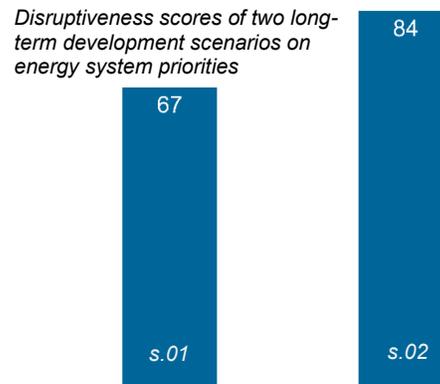


Fig. 4. Magnitude of disruption to energy system priorities induced by long-term risk and development scenarios

outlook using future energy resource projections. The methods identify the sub-basins that are most resilient in the context of alternative energy generation as well as sub-basins at risk of future disruptions to energy production. The results show that consideration of forward-looking climatological projections, as opposed to strictly historical observations of these metrics, greatly disrupts the priorities and order of the components of an energy system. In particular, the fossil-fueled development scenario, *s.02 - SSP 585* induces more extreme volatility in system priorities than the scenario representing less energy intensive development, *s.01 - SSP 126*, although both result in considerable changes to current system priorities. By introducing these future projections data, this work presents data-driven methods for risk-informed decision-making and resilience planning. This study defined an energy system by 27 components, namely the 27 hydrological sub-basins either partially or wholly contained within Turkmenistan. This definition of the system was primarily driven by a review of the related literature and the availability of both the historical and forward looking projections data. Future work will consider the potential of other geographic delineations of the system, such as the provinces and districts of Turkmenistan, to assess system risk and resilience. Additional work is planned to explore the sensitivity of the methods to the choice of projection models and time horizons by considering multiple projection models, ensemble models, intermediate time horizons, and additional SSP scenarios.

REFERENCES

- [1] Intergovernmental Panel On Climate Change (Ippc), *Climate Change 2022 – Impacts, Adaptation and Vulnerability: Working Group II Contribution to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*, 1st ed. Cambridge University Press, 2023. doi: 10.1017/9781009325844.
- [2] R. Sabyrbekov, I. Overland, and R. Vakulchuk, Eds., *Climate Change in Central Asia: Decarbonization, Energy Transition and Climate Policy*. in SpringerBriefs in Climate Studies. Cham: Springer Nature, 2023.
- [3] “Voluntary National Review of Turkmenistan on the progress of implementation of the Global Agenda for Sustainable Development,” Turkmen State Publishing Service, Ashgabat, 2023. Accessed: Feb. 03, 2025. [Online]. Available: <https://turkmenistan.un.org/sites/default/files/2023-07/VNR-2023%20Turkmenistan%20Report%20EN.pdf>
- [4] S. Berdimuhamedow, “STATEMENT by the President of Turkmenistan at the 28th session of the Conference of the Parties to the UN Framework Convention of climate change.” UNFCCC, Dec. 01, 2023. Accessed: Feb. 03, 2025. [Online]. Available: https://unfccc.int/sites/default/files/resource/TURKMENISTAN_cop28c mp18cma5_HLS_ENG.pdf
- [5] P. Ahmet, “Roadmap for Greening the Economy of Turkmenistan,” *IgMin Res.*, vol. 2, no. 5, pp. 341–347, May 2024, doi: 10.61927/igmin184.
- [6] Climate and Clean Air Coalition, “Global Methane Pledge,” *Global Methane Pledge*. Accessed: Feb. 05, 2025. [Online]. Available: <https://www.globalmethanepledge.org/>
- [7] “Turkmenistan - Country Factsheet,” *The World Factbook*. Central Intelligence Agency, Jan. 16, 2025. Accessed: Feb. 05, 2025. [Online]. Available: <https://www.cia.gov/the-world-factbook/countries/turkmenistan/factsheets/>
- [8] World Bank Group, “The World Bank in Turkmenistan,” *World Bank*. Accessed: Feb. 05, 2025. [Online]. Available: <https://www.worldbank.org/en/country/turkmenistan/overview>
- [9] International Energy Agency, “Turkmenistan - Overview,” *IEA*. Accessed: Feb. 05, 2025. [Online]. Available: <https://www.iea.org/countries/turkmenistan>
- [10] OECD, *Green Finance and Investment Sustainable Infrastructure for Low-Carbon Development in Central Asia and the Caucasus Hotspot Analysis and Needs Assessment*. Paris: OECD Publishing, 2019.
- [11] U.S. Energy Information Administration, “Turkmenistan,” *International - U.S. Energy Information Administration (EIA)*. Accessed: Feb. 05, 2025. [Online]. Available: <https://www.eia.gov/international/analysis/country/TKM>
- [12] H. Myrat and Y. Z. Jun, “Natural Gas Trade between Turkmenistan and China in the Context of the BRI,” *Int. J. Bus. Mark. Manag. IJBMM*, vol. 8, no. 6, pp. 121–130, Nov. 2023.
- [13] M. Laldjebaev, R. Isaev, and A. Saukhimov, “Renewable energy in Central Asia: An overview of potentials, deployment, outlook, and barriers,” *Energy Rep.*, vol. 7, pp. 3125–3136, Nov. 2021, doi: 10.1016/j.egy.2021.05.014.
- [14] R. Satymov, D. Bogdanov, and C. Breyer, “The Value of Fast Transitioning to a Fully Sustainable Energy System: The Case of Turkmenistan,” *IEEE Access*, vol. 9, pp. 13590–13611, 2021, doi: 10.1109/ACCESS.2021.3050817.
- [15] A. Bahrami, A. Teimourian, C. O. Okoye, and N. Khosravi, “Assessing the feasibility of wind energy as a power source in Turkmenistan; a major opportunity for Central Asia’s energy market,” *Energy*, vol. 183, pp. 415–427, Sep. 2019, doi: 10.1016/j.energy.2019.06.108.
- [16] A. Abylkasymova, Farkhod Aminjonov, D. Moldokanov, R. Vakulchuk, I. Overland, and Bahtiyor Eshchanov, “Renewable Energy Policies of the Central Asian Countries,” *Cent. Asia Reg. Data Rev.*, vol. 16, pp. 1–4, Feb. 2019, doi: 10.13140/RG.2.2.16609.56166/1.
- [17] B. Lehner and G. Grill, “Global river hydrography and network routing: baseline data and new approaches to study the world’s large river systems,” *Hydrol. Process.*, vol. 27, no. 15, pp. 2171–2186, 2013, doi: 10.1002/hyp.9740.
- [18] V. Eyring et al., “Overview of the Coupled Model Intercomparison Project Phase 6 (CMIP6) experimental design and organization,” *Geosci. Model Dev.*, vol. 9, no. 5, pp. 1937–1958, May 2016, doi: 10.5194/gmd-9-1937-2016.
- [19] Intergovernmental Panel On Climate Change (Ippc), *Climate Change 2021 – The Physical Science Basis: Working Group I Contribution to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*, 1st ed. Cambridge University Press, 2023. doi: 10.1017/9781009157896.
- [20] K. Riahi et al., “The Shared Socioeconomic Pathways and their energy, land use, and greenhouse gas emissions implications: An overview,” *Glob. Environ. Change*, vol. 42, pp. 153–168, Jan. 2017, doi: 10.1016/j.gloenvcha.2016.05.009.
- [21] B. Thrasher, W. Wang, A. Michaelis, F. Melton, T. Lee, and R. Nemani, “NASA Global Daily Downscaled Projections, CMIP6,” *Sci. Data*, vol. 9, no. 1, p. 262, Jun. 2022, doi: 10.1038/s41597-022-01393-4.
- [22] M. C. Marcellin et al., “Systems analysis for energy assets of Iraq influenced by water scarcity,” *Environ. Syst. Decis.*, vol. 44, no. 2, pp. 259–279, Jun. 2024, doi: 10.1007/s10669-024-09967-w.
- [23] M. C. Marcellin et al., “Risk and Systems Analysis for Renewable Power Generation with Environmental and Other Stressors,” *INCOSE Int. Symp.*, vol. 34, no. 1, pp. 631–648, Jul. 2024, doi: 10.1002/iis2.13167.
- [24] D. A. Johnson et al., “Environmental Security and Resilience of Transportation System and Supply Chains for Iraq,” in *2024 10th International Conference on Control, Decision and Information Technologies (CoDIT)*, Valletta, Malta: IEEE, Jul. 2024, pp. 479–485. doi: 10.1109/CoDIT62066.2024.10708123.
- [25] R. A. Rebar et al., “Systemic Risk Analysis of Agriculture with Climate and Other Stressors,” in *2024 IEEE International Systems Conference (SysCon)*, Montreal, QC, Canada: IEEE, Apr. 2024, pp. 1–8. doi: 10.1109/SysCon61195.2024.10553574.
- [26] F. Lv and H. Tang, “Assessing the impact of climate change on the optimal solar–wind hybrid power generation potential in China: A focus on stability and complementarity,” *Renew. Sustain. Energy Rev.*, vol. 212, p. 115429, Apr. 2025, doi: 10.1016/j.rser.2025.115429.
- [27] A. Damiani, N. N. Ishizaki, H. Sasaki, S. Feron, and R. R. Cordero, “Exploring super-resolution spatial downscaling of several meteorological variables and potential applications for photovoltaic power,” *Sci. Rep.*, vol. 14, no. 1, p. 7254, Mar. 2024, doi: 10.1038/s41598-024-57759-8.
- [28] G. Esnaola, A. Ulazia, J. Sáenz, and G. Ibarra-Berastegi, “Future changes of global annual and seasonal wind-energy production in CMIP6 projections considering air density variation,” *Energy*, vol. 307, p. 132706, Oct. 2024, doi: 10.1016/j.energy.2024.132706.
- [29] S. M. Shalaby, M. K. Elfakharany, B. M. Moharram, and H. F. Abosheisha, “Experimental study on the performance of PV with water cooling,” *Energy Rep.*, vol. 8, pp. 957–961, Apr. 2022, doi: 10.1016/j.egy.2021.11.155.
- [30] S. Dubey, J. N. Sarvaiya, and B. Seshadri, “Temperature Dependent Photovoltaic (PV) Efficiency and Its Effect on PV Production in the World – A Review,” *Energy Procedia*, vol. 33, pp. 311–321, 2013, doi: 10.1016/j.egypro.2013.05.072.
- [31] L. Ashok Kumar, V. Indragandhi, Y. Teekaraman, R. Kuppusamy, and A. Radhakrishnan, “Design and Implementation of Automatic Water Spraying System for Solar Photovoltaic Module,” *Math. Probl. Eng.*, vol. 2022, pp. 1–11, Jan. 2022, doi: 10.1155/2022/7129.