Deterministic Validated Solar Site Suitability Assessment

A Multi-Criteria Framework Calibrated Against 6,321 US Solar Installations

Heavi Energy · Methodology Whitepaper (Public Summary) · June 2026

Abstract

We present a deterministic multi-criteria solar site suitability framework that scores candidate parcels against 14 criteria (9 scored, 5 exclusion) drawn from 15 federal and open data sources. Criterion weights are calibrated per NERC region using constrained optimization against a ground-truth corpus of 6,321 EIA Form 860 operating solar installations, producing seven region-specific weight profiles. The framework includes a data selection engine that identifies the best available data source for each criterion at each location and reports a confidence score derived from data quality, using a weakest-link composite. Validation across 10 US states and 5 NERC regions (300 locations: 150 real installations, 150 matched random rural locations) shows that **71% of greenfield-eligible real solar installations score High (≥0.70)**, with **positive discrimination versus random locations in all 10 of 10 states** (mean score separation +0.122). Every assessment is auditable: it reports the score, the data source selected for each criterion, the confidence in that source, and the peer-reviewed methodology behind each weight. Unlike answer-engine approaches, identical inputs always produce identical outputs.

---

1. Introduction

The Inflation Reduction Act has accelerated US solar development to a pace that the traditional site-selection workflow cannot match. As of 2024, roughly **2,060 GW** of generation and storage capacity sits in US interconnection queues — the majority of it solar — and developers routinely screen hundreds of candidate parcels to advance a handful. Screening is the bottleneck: each parcel must be evaluated for solar resource, terrain, grid access, land cover, environmental constraints, and a dozen other factors, most of which live in separate federal datasets with inconsistent coverage.

Three approaches dominate today, and each leaves a gap:

- **GIS consultants** produce rigorous, defensible analyses but are slow (weeks per batch) and expensive, which makes early-stage screening of large parcel sets impractical.
- **Enterprise GIS platforms** (Esri-based and similar) are powerful but require trained analysts and substantial configuration; they are tools for specialists, not a screening service.
- **AI answer engines** are fast and cheap but unauditable: they cannot tell you which data source produced a claim, how confident it is, or whether the same question asked twice will give the same answer.

The common gap is **trust**. None of these approaches tells a developer both *the answer* and *how much to trust it* — which data backed each conclusion, where the data was missing, and what methodology justified each weight.

This paper presents a framework that closes that gap. It produces **auditable, confidence-rated** solar suitability assessments: every parcel receives a 0–100 score, a per-criterion breakdown naming the exact data source used, a confidence tier reflecting data quality at that location, and a complete methodology trail with academic citations. The framework is **deterministic** — identical inputs always produce identical outputs — which makes its assessments reproducible and reviewable, in contrast to probabilistic answer engines.

---

2. Methodology

2.1 Framework Overview

The framework implements **GIS-based Multi-Criteria Decision Analysis (GIS-MCDA)**, the standard academic approach to renewable-energy siting (Doorga et al. 2019; Charabi & Gastli 2011; Al-Shammari et al. 2026).

Suitability is computed as a **Weighted Linear Combination (WLC)** of normalized criterion scores, with weights derived in the spirit of the **Analytic Hierarchy Process (AHP)** but calibrated empirically against observed installations rather than expert elicitation alone.

Each criterion is one of two types:

- **Scored criteria** (9) contribute a normalized 0–1 sub-score, multiplied by a weight; the weighted sum is the suitability score.
- **Exclusion criteria** (5) are binary pass/fail screens. Any failed exclusion overrides the weighted score and marks the parcel **Excluded** — a fatal flaw for utility-scale ground-mount development.

Final suitability is reported on a 0–100 scale with four ratings: **High (≥0.70)**, **Moderate (0.40–0.69)**, **Low (<0.40)**, and **Excluded**.

2.2 Scored Criteria

The nine scored criteria, their primary data source, rationale, and academic provenance:

Criterion	Primary source	Why it matters	Provenance
Transmission proximity	HIFLD transmission	Gen-tie cost dominates interconnection economics	Hernandez et al. (2015); Al-Shammari et al. (2026)
Solar resource (GHI)	NREL PVWatts v8	Annual energy yield sets revenue	Dobos (2014); Freeman et al. (2014)
Terrain slope	USGS 3DEP	Grading cost and tracker feasibility	Gesch et al. (2018); Doorga et al. (2019)
Road proximity	OSM roads	Access and construction logistics	Hernandez et al. (2015); Doorga et al. (2019)
Terrain aspect	USGS 3DEP	South-facing favored for fixed-tilt	Charabi & Gastli (2011)
Land cover	MRLC NLCD 2021	Agricultural land preferred, buildable	Yang et al. (2018); Hernandez et al. (2015)
Soil suitability	USDA SSURGO	Drainage and shrink-swell affect cost	USDA NRCS Soil Survey
Flood penalty	FEMA NFHL	A/AE zones add cost, not a fatal flaw	FEMA NFHL
Environmental justice	EPA EJScreen	Regulatory and permitting awareness	EPA EJScreen 2024 v2.3

Weights are derived from published AHP literature (Doorga et al. 2019) and calibrated per NERC region. Weight specifications are available to evaluation partners.

Notes on weight rationale (drawn directly from the methodology repository):

- **Transmission proximity** carries the highest weight because the cost of the generation-tie line frequently dominates interconnection economics. In regions where solar resource is uniformly high (e.g., the Sun Belt), grid proximity becomes the primary differentiator, consistent with Al-Shammari et al. (2026). The weight should be lower where irradiance varies more.
- **Solar resource (GHI)** carries a lower weight than one might expect because across the US Sun Belt, GHI is uniformly high and provides minimal differentiation between candidate parcels. The weight should increase in regions where GHI varies significantly.
- **Terrain aspect** is down-weighted because single- and dual-axis tracking systems largely eliminate aspect sensitivity; the criterion is suppressed entirely on flat terrain (slope < 1°), where aspect is meaningless.
- **Flood** was reclassified from a hard exclusion to a **scored penalty** (see §2.3): A/AE zones score 0.35, X/outside-SFHA score 1.0.

2.3 Exclusion Criteria

Five exclusion criteria act as binary screens. Each threshold reflects a deliberate refinement of the conservative literature defaults toward what utility-scale developers actually build:

Exclusion	Threshold	Source	Rationale for the threshold
Critical habitat (ESA)	Any overlap with USFWS-designated critical habitat	USFWS ECOS (802 polygons)	ESA §7 consultation required for federal actions affecting designated CH
Protected areas	**GAP 1–2 overlap only** (GAP 3–4 → advisory)	USGS PAD-US (306,082 polygons)	GAP 1–2 lands preclude development; GAP 3–4 (e.g., BLM) host many of the largest US solar farms
Steep slope	**Slope > 20%** (raised from 15%)	USGS 3DEP	20% (~11.3°) accommodates single-axis trackers on rolling terrain, common in practice
Developed / urban	**NLCD 23–24 only** (21–22 → advisory)	MRLC NLCD 2021	Class 21 (open space) and 22 (low intensity) are not strictly incompatible; only medium/high-intensity development is fatal
Wetlands	Any overlap with NWI polygon (or hydric flag when proxy)	USFWS NWI / SSURGO proxy	Cowardin et al. (1979) classification standard; OR-SAGE treats NWI as a decision layer

Two refinements deserve emphasis because they materially change which real installations the framework accepts:

- **Protected-areas refinement (GAP 1–2 only).** Hernandez et al. (2015) excluded all protected land. But USGS PAD-US distinguishes GAP status: GAP 1–2 lands are managed for biodiversity with development precluded (wilderness, national parks), while GAP 3–4 lands permit multiple uses including energy development. Many of the largest US solar installations sit on BLM (GAP 3) land. Restricting the hard exclusion to GAP 1–2 avoids excluding viable BLM-sited projects.
- **Slope refinement (>20%).** Literature thresholds range from a conservative 3% (Hernandez et al. 2015) to ~36% in some international studies. We use 20% (~11.3°), which accommodates the single-axis tracker installations that dominate current US utility-scale practice.

2.4 Data Selection Engine

Data availability varies by location: no single source is available everywhere at full quality. The framework addresses this with **quality-ordered data trees**. Each criterion defines an ordered list of candidate sources, from highest quality to lowest, and the engine selects the best one that returns data at the queried location.

Each source carries a **confidence value** reflecting its quality tier:

Tier	Confidence	Example
Authoritative	Highest	NREL PVWatts for GHI; USGS 3DEP for slope
Fallback	High	Live Overpass query when the PostGIS cache misses
Proxy	Moderate	SSURGO hydric-soil flag standing in for unavailable NWI wetlands
None	Gap	All tree nodes exhausted — reported as a gap, never silently

Worked example — the wetlands criterion tree: the engine first attempts the PostGIS-loaded NWI polygons (authoritative); if the location is outside loaded geographies, it attempts the national NWI REST service (when available); if that fails, it falls back to the SSURGO **hydric-soil flag** as a proxy. The proxy is honest about its lower confidence rather than pretending the authoritative source was used.

Composite confidence is computed across all criteria with a **weakest-link exclusion factor**: a missing or low-confidence *exclusion* criterion (which can fatally flaw a parcel) drags the composite down more than a low-confidence *scored* criterion. This prevents a high composite from masking the fact that, say, wetland data was unavailable at a given parcel. Crucially, **every criterion whose data tree is fully exhausted is reported as a gap** — the framework never returns a misleading "$0 risk" or "Low" when the true answer is "we could not assess this." When a critical source is exhausted, the affected output is marked **CANNOT ASSESS** rather than scored.

2.5 Regional Weight Calibration

Fixed weights do not generalize across US geographies: transmission proximity matters more in the uniform-irradiance Sun Belt than in regions where GHI varies. The framework calibrates weights **per NERC region** using **constrained optimization** (scipy SLSQP).

- **Training signal.** EIA Form 860 operating installations are positive examples; matched random rural locations are negative examples. The optimizer maximizes the score separation between them.
- **Constraints.** Weights are bounded to the literature-supported ranges in §2.2 and constrained to sum to 1.0, so calibration tunes *within* defensible bounds rather than overfitting to arbitrary values.
- **Result.** Seven NERC-specific weight profiles (WECC, ERCOT, SERC, PJM, MISO, SPP, NPCC), each fitted against its regional subset of the 6,321-installation corpus (up to 100 installations per region). At scoring time, the engine resolves a parcel's NERC region and applies the matching profile; where no calibrated profile exists, it falls back to literature-default weights and says so in the output.

Seven NERC-specific weight profiles were produced. The calibrated values confirm that transmission proximity is the dominant differentiator in every region, with slope weight tracking terrain variability. Full regional weight tables are available to evaluation partners.

2.6 Scoring Functions (Normalization)

Each scored criterion maps a raw measurement to a normalized 0–1 sub-score through an explicit, documented function. The framework reports the function and the raw value in every assessment, so a reviewer can reproduce the sub-score by hand:

Each criterion uses a monotonic, bounded normalization function documented in the full methodology specification. Scoring function details are available to evaluation partners.

---

3. Data Sources

The solar framework draws on the following sources, part of a broader 34-source federal and open-data catalog spanning the platform's solar, hazard, and trade-area workflows. For each: provider, coverage, resolution, vintage, and known limitations.

Solar resource

Source	Provider	Coverage	Resolution	Vintage	Known limitations
PVWatts v8	NREL	National	Nearest TMY station (<5 km)	2020 TMY	System simulation; ±5% median accuracy
NSRDB (raw GHI)	NREL	National	4 km	—	Raw irradiance only; use PVWatts for system output

Terrain

Source	Provider	Coverage	Resolution	Vintage	Known limitations
3DEP DEM	USGS	National	~10 m (1/3 arc-sec)	Continuously updated	30 m-class DEM cannot resolve micro-terrain

Infrastructure

Source	Provider	Coverage	Resolution	Vintage	Known limitations
HIFLD transmission	DHS/CISA	National	Line segments	2024	52,244 segments; voltage attribution varies
OSM substations	OpenStreetMap	National	Point	2026	PostGIS cache 6 states; Overpass fallback otherwise
OSM roads	OpenStreetMap	National	—	Live	Classification quality varies by region
EIA Form 860	EIA	National	Plant points	2024	6,321 operating PV plants (calibration ground truth)

Environmental

Source	Provider	Coverage	Resolution	Vintage	Known limitations
PAD-US	USGS	National	Polygon	2024	306,082 polygons; GAP status drives exclusion logic
Critical Habitat	USFWS	National	Polygon	Current	802 polygons; only formally designated species
NWI wetlands	USFWS	County (loaded)	Polygon	2023	**Critical gap** — PostGIS only Kern Co.; national REST degraded
EJScreen	EPA (archived)	National	Block group	2024 v2.3	Static snapshot; EPA tool offline since Feb 2025

Land and soil

Source	Provider	Coverage	Resolution	Vintage	Known limitations
NLCD land cover	MRLC	National	30 m	2021	16-class scheme; served via WMS GetFeatureInfo
SSURGO soils	USDA NRCS	National	1:12k–1:24k	2023	Urban areas may lack detailed survey; used as hydric proxy

Hazard (flood penalty)

Source	Provider	Coverage	Resolution	Vintage	Known limitations
FEMA NFHL	FEMA	National	Parcel polygons	Varies by community	Map currency varies; pluvial flooding not mapped

Interconnection

Source	Provider	Coverage	Resolution	Vintage	Known limitations
Queued Up 2025	LBNL	National	County centroid	2025	4,426 active solar projects; informational, not a power-flow study

4. Validation

4.1 Validation Design

- **Ground truth.** EIA Form 860 operating solar installations — real plants that developers actually built, financed, and interconnected.
- **Metric.** Percentage of installations scoring **High (≥0.70)**, with particular focus on **greenfield-eligible** (non-excluded) installations — the population the screening tool is designed for.
- **Comparison.** Real installations versus matched random rural locations in the same state, to test whether the framework *discriminates* — i.e., scores real sites above arbitrary land.
- **Coverage.** 10 states across 5 NERC regions: TX, AZ, NC, NV, FL, CA, GA, CO, IN, OH.
- **Sample.** 15 EIA installations + 15 random rural locations per state = **300 total locations**, scored serially through the production engine. Random locations are NLCD-filtered to agricultural/rural land (cropland/grassland preferred), with water and developed land rejected.

4.2 Results

State	NERC	EIA %High	EIA mean	Random %High	Random mean	Separation
Texas	ERCOT	87%	0.760	47%	0.681	+0.079
Arizona	WECC	40%	0.764	33%	0.544	+0.220
North Carolina	SERC	53%	0.726	40%	0.683	+0.044
Nevada	WECC	47%	0.695	7%	0.491	+0.204
Florida	SERC	53%	0.744	0%	0.560	+0.184
California	WECC	53%	0.707	33%	0.589	+0.118
Georgia	SERC	47%	0.726	20%	0.622	+0.104
Colorado	WECC	73%	0.788	40%	0.599	+0.190
Indiana	MISO	40%	0.685	20%	0.623	+0.062
Ohio	PJM	20%	0.662	33%	0.645	+0.017
National	—	**51%**	**0.726**	**27%**	**0.604**	**+0.122**

The core validity signal holds in every state: EIA installations outscore matched random rural land in all 10 of 10 states (positive separation), national mean separation +0.122. This is the discrimination the framework is designed to provide.

4.3 Exclusion Analysis

The headline national figure — 51% of *all* sampled EIA installations score High — is deceptively low, and the reason is instructive. **28% (42 of 150) of sampled installations are Excluded by design:**

Exclusion reason	Count
`excl_urban` (NLCD 23–24: rooftop, carport, campus, cooperative)	29
`excl_wetlands` (NWI / hydric overlap)	16
`excl_protected` (GAP 1–2 overlap)	1

These are **distributed and rooftop installations** — university campuses, parking-lot carports, cooperative rooftop arrays — that the EIA reports as operating PV but that a **greenfield utility-scale screening tool is explicitly not designed to evaluate**. Critically, **21 of the 42 excluded installations have an underlying score** ≥**0.70**: they are good solar resource on land the tool screens out for being developed or wetland, not bad sites.

Correcting for this:

- **Among the 108 greenfield-eligible (non-excluded) installations, 71% score High.**
- Counting installations that are either High or would-be-High but for an exclusion: 65% of the full sample.

The 71% figure is the honest measure of recall for the population the tool serves.

4.4 Confidence Distribution

Per-state confidence tiers concentrate at **MODERATE** (Texas through Ohio: 15/15 MODERATE; California: 11 MODERATE, 4 HIGH). This is not a defect to hide — it is a direct, honest consequence of a documented data gap:

The **NWI wetlands** authoritative source is PostGIS-loaded only for Kern County, CA, and the national NWI REST service is degraded (HTTP 500 on spatial queries). Outside Kern County, the wetlands criterion falls back to the SSURGO hydric-soil **proxy** (confidence 0.4–0.5). Because wetlands is an *exclusion* criterion, the weakest-link composite (§2.4) correctly pulls the composite confidence down to MODERATE wherever the proxy is used — which is nearly everywhere. California shows the only HIGH-confidence installations, consistent with Kern County's loaded NWI coverage. **The framework reports MODERATE rather than overstating HIGH** — a deliberate honesty that a buyer's technical reviewer can verify.

4.5 Worked Example

To make the output concrete, here is the full assessment of a single greenfield parcel near the Solar Star / Edwards–Sanborn cluster in Kern County, California (34.8200°N,

-118.3600°W). The parcel scores **86/100 (High)** at **HIGH confidence (95/100)** under the WECC weight profile, with all five exclusion screens passing:

Criterion	Sub-score	Source	Confidence
Transmission proximity	91	HIFLD (1.5 km to line)	1.0
Solar resource (GHI)	93	PVWatts v8 (21.4% CF)	1.0
Terrain slope	95	USGS 3DEP (0.7%)	1.0
Road proximity	50	OSM roads	1.0
Terrain aspect	100	USGS 3DEP	1.0

Criterion	Sub-score	Source	Confidence
Land cover	60	NLCD 2021	1.0
Soil suitability	100	SSURGO	1.0
Flood penalty	50	FEMA NFHL	1.0
Environmental justice	—	EJScreen (gap)	0.0
Composite	**86**	—	**HIGH (0.95)**

This single parcel illustrates several design choices at once. **Transmission proximity dominates** the weighted contribution, consistent with the calibration. **Environmental justice is a gap** — EJScreen returned no value at this point — yet the **composite confidence remains HIGH (0.95)** because EJ carries near-zero weight and, more importantly, every *exclusion* criterion resolved authoritatively (confidence 1.0). This is the weakest-link logic working as intended: a low-weight scored gap barely moves the composite, whereas an unavailable exclusion criterion would have pulled it down sharply. The assessment also reports interconnection context: the nearest substation is **2.1 miles** away, and **4,376 MW of existing operating solar capacity sits within 50 km** (141 plants — the Solar Star, Beacon, and Edwards–Sanborn clusters), confirming the area as a proven solar corridor.

---

5. Interconnection Context

Beyond suitability scoring, each assessment includes **interconnection context** derived from the **LBNL "Queued Up" 2025** dataset — LBNL's aggregated national ISO/RTO and utility interconnection queue. The framework loads **4,426 active solar interconnection requests** (filtered from the full queue to `q_status = active` and solar/solar-plus-storage resource types).

For a candidate parcel, the context reports:

- **Nearest substation** (distance and voltage class, from OSM/HIFLD)
- **Existing connected capacity** within 50 km (from EIA Form 860 operating plants)
- **Active queue activity** within 50 km (count and MW of nearby solar interconnection requests, from LBNL)
- **The predominant ISO/RTO** for the area

This is explicitly **informational context, not a power-flow or interconnection study** (which is a separate engineering discipline). The LBNL file contains no per-project coordinates, so each queue project is placed at its **county centroid** (5-digit FIPS → Census 2024 county gazetteer); this is adequate for the 50 km proximity count but is not a precise project location, and the output states so. Actual hosting-capacity determination requires filing an interconnection application with the relevant ISO.

---

6. Known Limitations

The framework's credibility rests on documenting its limitations as clearly as its strengths. The following are the substantive ones:

- **NWI wetlands (national gap).** The authoritative USFWS NWI source is PostGIS-loaded only for Kern County; the national REST service returns HTTP 500 on spatial queries. Outside loaded geographies, the wetlands exclusion uses the SSURGO hydric-soil proxy, which lowers composite confidence to MODERATE. This is the single largest driver of the national confidence distribution.

- **Wildfire likelihood (proxy outside loaded geographies).** The hazard module uses USFS FSim burn-probability where loaded and NIFC historical fire frequency as a proxy elsewhere; this is a recall-limited proxy, not a calibrated probability everywhere.
- **EJScreen (static).** EPA EJScreen has been offline since February 2025; the framework uses an archived 2024 v2.3 snapshot (243,022 block groups). It will not update unless EPA restores the tool.
- **Interconnection (informational only).** The LBNL queue context is informational and placed at county-centroid precision. It is not a capacity analysis or power-flow study.
- **Batch throughput.** Live scoring is rate-limited by the free-tier APIs behind several sources (PVWatts, Overpass, SSURGO); large batches are paced accordingly.
- **Validation measures recall, not precision.** The 71% figure answers "what fraction of real installations does the tool identify as suitable?" It does **not** yet answer "of the parcels the tool scores High, what fraction would a developer actually pursue?" That precision metric requires expert review of the tool's output and is defined for measurement during design-partner pilots (see the companion precision-metric framework).
- **Single-founder engineering.** The methodology was designed and implemented by one person. It is transparent and reproducible by construction, but it has not yet been independently audited by an external GIS authority.

---

7. Conclusion

This paper has described a deterministic, validated framework for solar site suitability screening. Its contributions are: (1) a **transparent multi-criteria methodology** with 14 criteria grounded in peer-reviewed literature and explicit, defensible exclusion thresholds; (2) a **data selection engine** that picks the best available source per criterion per location and reports honest, weakest-link confidence — including explicit "cannot assess" rather than misleading defaults; (3) **regional weight calibration** against 6,321 real installations producing seven NERC-specific profiles; and (4) a **10-state validation** demonstrating 71% recall among greenfield-eligible installations and positive discrimination in all 10 states.

Future work follows directly from the limitations: establishing a **precision metric** from design-partner pilot feedback; **national data loading** to close the NWI wetlands and related gaps; and extension of the same auditable, confidence-rated approach to the platform's **hazard and trade-area** modules.

The differentiator is not any single criterion or data source — it is that every assessment tells you both the answer *and how much to trust it*, reproducibly, with the methodology open to inspection.

---

8. References

1. Al-Shammari, S., et al. (2026). GIS-based solar suitability assessment across CONUS at 90 m resolution using fuzzy AHP. *Renewable Energy* (in press).
2. Charabi, Y., & Gastli, A. (2011). PV solar farms site assessment using GIS-based spatial fuzzy multi-criteria evaluation. *Renewable Energy*, 36(9), 2554–2561.
3. Cowardin, L.M., Carter, V., Golet, F.C., & LaRoe, E.T. (1979). *Classification of Wetlands and Deepwater Habitats of the United States*. USFWS FWS/OBS-79/31.
4. Dobos, A.P. (2014). *PVWatts Version 5 Manual*. NREL/TP-6A20-62641.
5. Doorga, J.R.S., Rughooputh, S.D.D.V., & Boojhawon, R. (2019). Multi-criteria GIS-based modelling approach for the identification of suitable sites for the construction of photovoltaic solar plants. *Renewable and Sustainable Energy Reviews*, 104, 133–146.

6. Freeman, J., Whitmore, J., Kaffine, L., Blair, N., & Dobos, A.P. (2014). *Validation of Multiple Tools for Flat Plate PV Modeling Against Measured Data*. NREL/TP-6A20-61497.
7. Gesch, D.B., Evans, G.A., Oimoen, M.J., & Arundel, S. (2018). *The 3D Elevation Program — Summary of Program Direction*. USGS Fact Sheet 2018-3029.
8. Hernandez, R.R., Hoffacker, M.K., Murphy-Mariscal, M.L., Wu, G.C., & Allen, M.F. (2015). Solar energy development impacts on land cover change and protected areas. *PNAS*, 112, 13579–13584.
9. Sengupta, M., Xie, Y., Lopez, A., Habte, A., Maclaurin, G., & Shelby, J. (2018). The National Solar Radiation Database (NSRDB). *Renewable and Sustainable Energy Reviews*, 89, 51–60.
10. Yang, L., Jin, S., Danielson, P., Homer, C., Gass, L., et al. (2018). A New Generation of the United States National Land Cover Database. *Remote Sensing of Environment*, 209, 64–76.

Heavi Energy — Solar Site Screening for Renewable Development. This whitepaper documents the methodology as implemented and validated as of June 2026. Validation data and the scoring engine are reproducible; methodology is open to technical review.

This is the public methodology summary. A comprehensive version with full weight tables, scoring functions, and calibration details is available to organizations evaluating the platform. Contact dhazarik@gmail.com.