Computational Replication of Photometric Sensor Analysis: A Definitive Guide to the PhotonsToPhotos Methodology

1. Executive Summary and Theoretical Foundation

The objective of this comprehensive research report is to provide an exhaustive, expert-level technical blueprint for replicating the sensor analysis methodology developed by William (Bill) Claff for the *PhotonsToPhotos* (P2P) project. This document serves as the definitive reference for developers and researchers seeking to build Python-based analysis tools—leveraging libraries such as rawpy and libraw—that yield results mathematically identical to Claff's industry-standard benchmarks.

The P2P methodology represents a paradigm shift from traditional engineering metrics provided by image sensor manufacturers. While standard engineering metrics typically define Dynamic Range (DR) based on a Signal-to-Noise Ratio (SNR) of 1 (where the signal is indistinguishable from the noise floor), Claff's **Photographic Dynamic Range (PDR)** introduces a perceptual floor based on a target SNR that dynamically scales with sensor resolution and print size. This ensures that the metric reflects the actual usability of the image in a standardized physical format—typically an 8x10 inch print viewed at arm's length—rather than a microscopic, pixel-level analysis that unfairly penalizes high-resolution sensors.[1]

To successfully replicate this pipeline, one must move beyond simple metadata extraction and engage in rigorous statistical analysis of raw Bayer data. This involves the construction and analysis of **Photon Transfer Curves (PTC)** derived from image pairs to mathematically isolate Temporal Noise from Fixed Pattern Noise (FPN).[3] This report details the precise mathematical derivations, empirical constants, and algorithmic steps required to achieve 100% accuracy in replication.

1.1 The Philosophy of Photographic Dynamic Range

The central thesis of the PhotonsToPhotos methodology is that "Image Quality" is an area-dependent phenomenon. As sensor resolution increases, the noise visible at the pixel level becomes less significant when the image is viewed at a constant size. Standard Engineering Dynamic Range (EDR) fails to account for this integration effect. EDR measures the dynamic range of a single pixel, implying that a 100-megapixel sensor with slightly noisier pixels is "worse" than a 12-megapixel sensor with cleaner pixels, even if the 100-megapixel image looks cleaner when printed.

PDR corrects this by normalizing the circle of confusion (CoC). It asks: "At what signal level does the *print* exhibit an SNR of 20?" This question requires a translation of noise characteristics from the native sensor resolution to a standardized viewing condition. This normalization is not applied as a post-processing "bonus" but is intrinsic to the calculation of the target SNR threshold used to define the shadow limit of the dynamic range.[5]

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2. Fundamental Sensor Physics and Noise Models

To replicate the P2P methodology, one must first implement a noise model that accurately reflects the physical processes of photon capture and signal readout. The P2P pipeline does not rely on manufacturer specifications (which are often misleading) but measures these physical properties directly from the raw data.

2.1 The Signal Chain

The signal S measured in Analog-to-Digital Units (ADU) or Digital Numbers (DN) is the result of a linear transformation of the incident photon flux, subjected to various noise sources. The governing equation for the signal recorded at a pixel (x,y) is:

$$S_{ADU}(x,y) = K \cdot (N_{photons} \cdot QE) + N_{read} + N_{fixed} + \text{Offset}$$

Where:

- $N_{photons}$ is the number of incident photons.
- QE is the Quantum Efficiency (electrons per photon).
- K is the System Gain (ADU per electron).
- N_{read} is the temporal Read Noise introduced by the readout electronics.
- N_{fixed} is the Fixed Pattern Noise (PRNU + DSNU).
- Offset is the Black Level offset added to prevent clipping of negative noise values.

2.2 Temporal vs. Spatial Noise

A critical distinction in the P2P methodology is the separation of Temporal Noise from Spatial Noise.

- **Temporal Noise** varies from frame to frame. It includes Photon Shot Noise (inherent to light) and Read Noise (thermal/electronic fluctuations).
- **Spatial Noise (FPN)** is constant across frames at the same exposure settings. It includes Photo Response Non-Uniformity (PRNU) and Dark Signal Non-Uniformity (DSNU).

Standard variance analysis on a single image lumps these two together:

$$\sigma^2_{total} = \sigma^2_{temporal} + \sigma^2_{spatial}$$

To construct an accurate Photon Transfer Curve (PTC) for gain calculation, one must isolate $\sigma^2_{temporal}$. Claff's methodology achieves this strictly through the **difference of image pairs**.[3] By subtracting two identical exposures, the constant spatial noise cancels out, and the variance of the difference image represents twice the temporal variance:

$$\text{Var}(Image_1 - Image_2) = \text{Var}(Noise_{temporal,1} - Noise_{temporal,2})$$

$$\text{Var}(Image_1 - Image_2) = \text{Var}(Noise_{temporal,1}) + \text{Var}(Noise_{temporal,2})$$

$$\text{Var}(Image_1 - Image_2) = 2 \cdot \sigma^2_{temporal}$$

Thus, the fundamental estimator for temporal noise variance in P2P is:

$$\sigma^2_{temporal} = \frac{\text{Var}(DifferenceFrame)}{2}$$

2.3 The Photon Transfer Curve (PTC)

The PTC is the engine of the P2P analysis. It plots Noise (or Variance) against Signal.

- **Regime 1: Read Noise Limited.** At low signals, noise is dominated by the constant read noise floor. The curve is flat (log-log slope 0).
- **Regime 2: Shot Noise Limited.** As signal increases, photon shot noise dominates. Since photon statistics follow a Poisson distribution, the variance of the electron count equals the mean electron count ($\sigma^2_e = S_e$). In the ADU domain, this manifests as a linear relationship between Variance (ADU^2) and Signal (ADU) with a slope equal to the Gain K.
- **Regime 3: Saturation.** As the full well capacity is reached, the variance typically plummets because the signal is clipped at the maximum ADU value.

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3. Data Acquisition Strategy

The quality of the analysis is entirely dependent on the quality of the input data. Claff's "Gain Collaboration" instructions delineate a specific protocol designed to capture the full dynamic range of the sensor while allowing for the statistical separation of noise sources.

3.1 The "Seven Pairs" Protocol

To calculate gain and PDR, the P2P methodology requires a dataset that spans the linear response region of the sensor. The standard protocol involves capturing **7 pairs of images** (14 files total) at each ISO setting to be tested.[3]

- **Setup:** A uniform light source is essential. A computer monitor displaying a solid white field is the recommended target. The lens should be focused at infinity with the filter ring pressed against the screen to defocus the pixel structure of the monitor, ensuring a smooth, flat field.
- **Exposure Stacking:** The pairs are taken at exposure intervals of 1/3 EV.
  - **Pair 1:** "Correct" exposure (mid-tone).

    - **Pair 2:** +1/3 EV.
    - **Pair 3:** +2/3 EV.
    - ...
    - **Pair 7:** +2 EV (near saturation but not clipped).
- **Rationale:** This spread ensures that data points are collected across the "Shot Noise Limited" regime, which is required for the linear regression used to determine Gain. If points are too low, Read Noise distorts the slope. If points are too high, saturation non-linearities distort the slope.

3.2 Dark Frames

In addition to the illuminated flat fields, the methodology requires **Dark Frames** (lens cap on, fastest shutter speed) to measure the Read Noise floor independent of photon noise. While Optical Black pixels are preferred (see Section 5), Dark Frames are necessary for cameras that crop the OB area or for cross-verification.[7]

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4. Raw Decoding and Pre-Processing

The implementation of the tool using rawpy (a Python wrapper for libraw) requires precise configuration to ensure that the data remains "raw." Most raw converters apply silent corrections that will invalidate the scientific analysis.

4.1 Libraw Configuration

The goal is to extract the unadulterated Bayer data.

- **Demosaicing:** Must be disabled. The analysis is performed on the Bayer CFA mosaic directly. Interpolation introduces spatial correlations that depress noise measurements.
    - rawpy flag: demosaic_algorithm=None or user_sat=None.
- **White Balance:** Must be disabled. Applying white balance multipliers scales the noise and signal differently across channels, breaking the Poisson relationship.
    - rawpy flag: camera_white_balance=False, no_auto_scale=True.
- **Black Level Subtraction:** This is a nuanced point. For PDR calculation, we need the signal relative to zero light. However, for noise analysis (calculating standard deviation), the absolute offset doesn't matter.
    - **Recommendation:** Extract the full raw image including the Optical Black border if possible. If rawpy automatically crops to the "Active Area" (which is default), you must query the black_level_per_channel attribute to manually subtract the offset later. Do *not* let rawpy clamp negative values to zero.
- **Data Type:** Ensure the output is not compressed to 8-bit. Use 16-bit unsigned integer arrays (uint16) or cast immediately to 64-bit floats (float64) for precision during variance calculation.

4.2 Handling the Bayer Pattern

The analysis must be performed on each color channel independently. A standard Bayer pattern (RGGB) contains four distinct channels: Red, Green1, Green2, and Blue.

- **Separation:** The raw array must be sliced into four sub-arrays.
    - Red: raw[0::2, 0::2]
    - Green1: raw[0::2, 1::2]
    - Green2: raw[1::2, 0::2]
    - Blue: raw[1::2, 1::2]
- **Independent Analysis:** P2P analyzes these as four separate sensors. This is critical because digital scaling (discussed in Section 6) often affects Red and Blue channels differently than Green.[3]

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5. Statistical Analysis of Read Noise

Read Noise is the fundamental limit of low-light performance. Determining it accurately requires handling statistical anomalies specific to certain camera manufacturers.

5.1 Optical Black (OB) vs. Metadata

Claff's tools prioritize the measurement of the **Optical Black (OB)** area—the masked pixels at the edge of the sensor used by the camera to establish the black level.[8]

- **Why OB?** The BlackLevel tag in the EXIF metadata is a static integer (e.g., 1024 or 512). However, the actual black level floats due to thermal drift and amplifier instability. Measuring the OB area for every frame provides the true, instantaneous zero-point.
- **Implementation:** Identify the OB margins using libraw's masking data. Calculate the mean of these pixels to determine the ZeroPoint and the standard deviation to estimate the ReadNoise.

5.2 The "Zero-Clipping" Problem (Nikon/Sony)

A major hurdle in replicating P2P accuracy is handling cameras that clip raw data at zero. In many Nikon and some Sony implementations, the camera firmware subtracts the black level and then clamps any resulting negative values to 0 before writing the raw file.[7]

- **The Artifact:** This results in a "half-Gaussian" histogram. A simple standard deviation calculation on this clipped data will severely underestimate the true noise (by a factor of roughly 0.6).
- **The Solution (Robust Estimator):** Claff utilizes a symmetry assumption. Since Read Noise is Gaussian, the distribution should be symmetric around the mode.
    - **Algorithm:**
        1. Compute the histogram of the dark data.
        2. Identify the Mode (peak).
        3. Discard the data to the left of the Mode (the clipped side).
        4. Mirror the data to the right of the Mode onto the left side.
        5. Calculate the standard deviation of this reconstructed "full" histogram.
    - **Alternative:** Use the **Median Absolute Deviation (MAD)**, which is a robust estimator of scale, though the mirrored histogram method is preferred for its

reconstruction capability.

5.3 Outlier Rejection

The OB area often contains "hot pixels" or defects. To prevent these from inflating the Read Noise measurement, a robust filtering step is required.[9]

- **Z-Score Filter:** Calculate the mean and standard deviation. Compute the Z-score for every pixel: $Z_i = (x_i - \mu) / \sigma$.
- **Threshold:** Exclude pixels with $|Z| > 4.0$ (or 5.0).
- **Recalculation:** Re-calculate the mean and standard deviation on the filtered set. This filtered standard deviation is the ReadNoise_ADU.

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6. System Gain Calculation

The System Gain (K) converts the abstract ADU values into physical units (electrons). This is derived from the Photon Transfer Curve constructed from the image pairs.

6.1 The Mathematical Model

We utilize the linear relationship in the Shot Noise regime:

$$\sigma^2_{ADU} = K \cdot (S_{ADU} - S_{Black}) + N_{read,ADU}^2$$

This is a classic linear equation of the form $y = mx + c$, where:

- $y = \sigma^2_{ADU}$ (Temporal Variance).
- $x = S_{ADU} - S_{Black}$ (Signal).
- $m = K$ (Gain in ADU/e-).
- $c = N_{read,ADU}^2$ (Read Noise Variance).

6.2 Implementation Steps

1. **Data Preparation:** For each of the 7 image pairs, extract a central crop (e.g., 200x200 pixels) to avoid lens vignetting (which acts as a variable signal across the frame).[3]
2. **Calculation:**
   - Compute the mean signal of the crop (S).
   - Compute the difference frame ($D = I_1 - I_2$).
   - Compute the variance of D and divide by 2: $\sigma^2 = \text{Var}(D)/2$.
3. **Regression:** Perform a linear least-squares regression on the set of (S, σ^2) points.
4. **Filtering:** It is crucial to exclude points that are too close to the noise floor (where Read Noise dominates and linearity is shaky) or too close to saturation (where Partial Well Filling reduces variance). Claff typically relies on the middle 3-4 pairs that show the highest correlation coefficient (R^2).

6.3 Gain Units

The slope m from the regression is the Gain in ADU/e-.
Most P2P charts present Unity ISO or Gain in e-/ADU.

- **Gain (e-/ADU):** Simply the inverse of the slope: $g = 1/m$.
- This value tells you how many electrons are required to generate 1 ADU. At Base ISO, this might be 3 or 4 e-/ADU. At High ISO, it often drops below 1 e-/ADU (meaning 1 electron generates multiple ADUs).

6.4 Digital Scaling Detection

By analyzing the four channels separately, one can detect digital scaling. If the Red and Blue channels show a Gain (K) that is exactly $1.2x$ or $1.5x$ higher than the Green channel, while the Read Noise scales similarly, it indicates that the camera is applying a digital multiplier to white balance the raw data before writing it.[3] P2P methodology notes this but typically reports the Green channel gain as the "True" analog gain of the sensor.

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7. Photographic Dynamic Range (PDR)

We now arrive at the core metric requested. PDR is the defining output of the PhotonsToPhotos project. It differentiates itself from Engineering Dynamic Range (EDR) by imposing a perceptual standard.

7.1 The PDR Definition

Photographic Dynamic Range is defined as the log-base-2 ratio of the **Full Well Capacity (Saturation Signal)** to the **Low Signal (S_{low})** where the Signal-to-Noise Ratio (SNR) equals a resolution-dependent target.

$$PDR = \log_2 \left(\frac{S_{max} - S_{Black}}{S_{low}} \right)$$

7.2 The Target SNR Formula

The "100% accuracy" requirement hinges on using the exact target SNR formula. P2P does not use a fixed $SNR=20$ for all sensors. It uses a sliding scale based on the sensor's vertical resolution.[5]

$$SNR_{target} = \frac{16000}{h_{sensor}}$$

Where h_{sensor} is the height of the active sensor area in pixels.
Derivation and Context:

- **Reference Standard:** The standard is based on an **8x10 inch print** viewed at a distance of approximately **25 cm (arm's length)**.
- **Visual Acuity:** The human eye can resolve a certain contrast ratio at this distance. The P2P methodology empirically determined that for a reference image height of roughly

800 pixels (corresponding to low-res print requirements), a pixel-level SNR of 20 is required for "excellent" quality.

- **Scaling Law:** As sensor resolution increases, the pixels in the print become smaller than the eye's circle of confusion (CoC). The eye effectively integrates multiple sensor pixels into one "visual pixel." This averaging process reduces noise by the square root of the number of pixels averaged.
- **The Constant:** The constant 16000 is derived from this relationship. For a sensor with height h, the SNR required at the pixel level to achieve the equivalent of "SNR=20 on the print" is reduced.
  - Example: A 24MP sensor (approx 4000px height).

    $$SNR_{target} = \frac{16000}{4000} = 4$$

    We only need a pixel-level SNR of 4 to achieve a print-level perceptual quality equivalent to the reference.
  - Example: A 60MP sensor (approx 6300px height).

    $$SNR_{target} = \frac{16000}{6300} \approx 2.5$$

    The threshold is lower, allowing the "usable" dynamic range to extend deeper into the shadows.

7.3 Solving for S_{low}

You cannot simply look up where SNR crosses the target because noise is a curve. You must mathematically solve for the signal level S_{low}.

1. Total Noise Model:

   $$N_{total}(S) = \sqrt{N_{read,e}^2 + S_e + (PRNU \cdot S_e)^2}$$

   (Expressed in electrons).
   Since we are looking for the low-light limit, PRNU is negligible.

   $$N_{total}(S) \approx \sqrt{N_{read,e}^2 + S_e}$$
2. SNR Equation:

   $$SNR(S) = \frac{S_e}{N_{total}(S)} = \frac{S_e}{\sqrt{N_{read,e}^2 + S_e}}$$
3. The Solver:
   We set $SNR(S) = SNR_{target}$ and solve for S_e.

   $$T = SNR_{target}$$
   $$T = \frac{S_e}{\sqrt{N_{read,e}^2 + S_e}}$$

   Square both sides:

$$T^2 = \frac{S_e^2}{N_{read,e}^2 + S_e}$$
$$T^2 (N_{read,e}^2 + S_e) = S_e^2$$

Rearrange into a standard quadratic equation ($ax^2 + bx + c = 0$):

$$S_e^2 - T^2 \cdot S_e - T^2 \cdot N_{read,e}^2 = 0$$

4. Quadratic Solution:

$$S_{low, e} = \frac{T^2 + \sqrt{(T^2)^2 - 4(1)(-T^2 N_{read,e}^2)}}{2}$$
$$S_{low, e} = \frac{T^2 + \sqrt{T^4 + 4 T^2 N_{read,e}^2}}{2}$$
This $S_{low, e}$ is the signal in electrons where the PDR floor is reached.

5. Calculate PDR:

$$PDR_{EV} = \log_2 \left(\frac{Saturation_{e}}{S_{low, e}} \right)$$

7.4 Normalization (Print PDR) vs. Pixel PDR

The user asked if the formula is $PDR_{print} = PDR_{pixel} + \log_2(...)$.
While mathematically one can convert between them, the P2P methodology calculates Print PDR directly by using the $16000/h$ target.

- If you used a fixed target of $SNR=20$ for S_{low}, you would calculate **Pixel PDR**.
- By using $SNR=16000/h$, you inherently calculate **Print PDR**.
- There is no need for a secondary normalization step if the target is set correctly at the start. The "Normalization" is intrinsic to the target SNR selection. This is the "100% accurate" method used by Claff.[5]

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8. Secondary Metrics and Derived Scores

8.1 Low Light ISO Score

The **Low Light ISO** score (similar to the "Sports" score on other sites) is a single integer value summarizing the low-light capability of the sensor.

- **Definition:** The ISO setting at which the PDR drops to exactly **6.5 EV**.[10]
- **Rationale:** 6.5 EV of dynamic range is considered the minimum acceptable threshold for high-quality publication of sports/action photography where lighting is poor and shutter speeds are fast.
- **Calculation:**
    1. Compute PDR for every whole ISO step (100, 200, 400,...).
    2. Plot PDR (y) vs ISO (x) on a log-log scale.
    3. Identify the two data points (ISO_1, PDR_1) and (ISO_2, PDR_2) that bracket the value 6.5.
    4. Perform a linear interpolation in log-log space:

$$\text{Slope} = \frac{\log(PDR_2) - \log(PDR_1)}{\log(ISO_2) - \log(ISO_1)}$$

$$\log(ISO_{LowLight}) = \log(ISO_1) + \frac{\log(6.5) - \log(PDR_1)}{\text{Slope}}$$

$$ISO_{LowLight} = 10^{\log(ISO_{LowLight})}$$

8.2 Shadow Improvement

This metric helps users determine if their camera is "ISO Invariant" (or "ISOless").

- **Concept:** Raising ISO via analog gain reduces Read Noise (in input-referred electrons), improving shadow quality. However, above a certain ISO, many cameras switch to digital gain, which stops improving Read Noise while clipping highlights.
- Calculation:
  For a given ISO x, the Shadow Improvement is the difference between the measured PDR at ISO x and the PDR one would expect if the Read Noise had remained constant (in DN) from the Base ISO.
  Alternatively, Claff plots the Input-Referred Read Noise vs ISO. The point where this curve flattens is the point of diminishing returns.
  In P2P charts, Shadow Improvement is explicitly the difference in dynamic range gained by increasing analog amplification versus shooting at base ISO and brightening in post.[11]

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9. Implementation Guide: Python Logic

This section translates the theoretical framework into a concrete structural logic for your Python tool.

9.1 Dependency Management

Use rawpy for decoding. Ensure you have numpy for array manipulation and scipy.stats for linear regression and robust statistics.

9.2 The SensorAnalyzer Class Structure

Python

```python
class SensorAnalyzer:
    def __init__(self, raw_pairs):
        """
        raw_pairs: Dictionary mapping ISO to a list of file path tuples (pair1_a, pair1_b),...
        """
        self.raw_pairs = raw_pairs
```

```
        self.results = {}

    def analyze_iso(self, iso):
        # 1. Gain Calculation
        signal_adu =
        variance_adu =

        for file_a, file_b in self.raw_pairs[iso]:
            # Load RAWs without processing
            # Extract Green channel (or average)
            # Calculate Mean Signal (S)
            # Calculate Difference Variance / 2
            signal_adu.append(S)
            variance_adu.append(Var)

        # Linear Regression
        # Slope = Gain (ADU/e-)
        gain_adu_e = linregress(signal_adu, variance_adu).slope

        # 2. Read Noise Calculation
        # Load a Dark Frame or use OB from one of the files
        # Extract OB area
        # Perform Robust Std Dev (Mirroring method if clipped)
        rn_adu = robust_std(ob_pixels)
        rn_e = rn_adu / gain_adu_e

        # 3. PDR Calculation
        # Get Sensor Height
        h = raw_height
        target_snr = 16000 / h

        # Solve Quadratic for S_low (electrons)
        # s^2 - T^2*s - T^2*rn_e^2 = 0
        delta = (target_snr**2)**2 - 4 * 1 * (-(target_snr**2) * rn_e**2)
        s_low_e = (target_snr**2 + sqrt(delta)) / 2

        # Get Saturation
        sat_adu = white_level - black_level
        sat_e = sat_adu / gain_adu_e

        pdr = log2(sat_e / s_low_e)

        return {
```

```
        "ISO": iso,
        "Gain_e_ADU": 1/gain_adu_e,
        "ReadNoise_e": rn_e,
        "PDR": pdr
    }
```

9.3 Validation Requirements

To ensure "100% accuracy," you must validate your tool against the published data on Photonstophotos.net.

1. **Select a Reference Camera:** Choose a common model like the Nikon D850 or Sony A7III.
2. **Download Reference Data:** Get the PDR and Read Noise charts from the P2P website (available as CSVs or interactive charts).
3. **Run Your Tool:** Process your own set of pairs for the same camera.
4. **Compare:** Your Gain should be within 5% (due to sample variation). Your PDR should be within 0.1 EV. If your PDR is consistently off by ~0.5 EV, check your Black Level subtraction or your Target SNR formula ($16000/h$).

10. Conclusion

Replicating Bill Claff's PhotonsToPhotos methodology is a rigorous exercise in signal processing. It requires discarding the simplified "engineering" view of sensors in favor of a "photographic" view that accounts for the area-dependent nature of image quality.
By strictly adhering to the **Seven Pairs Protocol**, utilizing **Difference Frames** to isolate temporal noise, detecting and correcting for **Zero-Clipping**, and applying the precise **$16000/height$** SNR target, your Python-based tool will be able to generate sensor metrics that are directly comparable to the P2P database. This consistency enables the meaningful comparison of sensors across different resolutions and formats, providing true insight into their photographic potential.

Metric	**Core Dependency**	**Key Formula / Value**
Gain (K)	Image Pairs (1/3 EV steps)	Slope of Var_{ADU} vs Signal_{ADU}
Read Noise (N_r)	Optical Black (OB)	Robust Std Dev of OB area (Mirrored Histogram)
PDR Target (T)	Sensor Resolution	$SNR_{target} = 16000 / Height_{pixels}$
PDR Score	Saturation & Target	$\log_2(S_{max} / S_{low})$
Low Light ISO	PDR Curve	Interpolated ISO at PDR = 6.5 EV

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