**Spoilage Risk Calculation Methodology**

The spoilage risk in the Surplus2Serve machine learning model is calculated through a multi-factorial approach that considers several key variables affecting produce degradation. Here is how the risk calculation works:

**Base Risk Calculation**

The model starts with a baseline spoilage risk of 0.0 and adjusts it based on multiple factors:

**Environmental Factors**

**Temperature impact**:

* If temperature exceeds 30°C: Risk increases by **(temperature - 30) × 0.1.**
* If temperature is below 25°C: Risk decreases by **(25 - temperature) × 0.05.**

**Temperature Range Selection in the Spoilage Risk Model**

The temperature range of 20-37°C used in the model was carefully selected to represent environmental conditions in India while capturing the critical temperature thresholds that affect produce spoilage. Here is the reasoning behind this specific range:

**Physiological and Environmental Basis**

1. **Lower Bound (20°C)**:

* Represents a cool but common temperature in many Indian regions.
* Most microbial growth slows significantly below 20°C.
* Reflects typical cold storage or winter temperatures in many parts of India.
* Below this temperature, the spoilage dynamics change significantly and would require different modelling approaches.

1. **Upper Bound (37°C)**:

* Represents common high temperatures during Indian summers.
* Approximates human body temperature, which is a critical physiological threshold for many microorganisms.
* Many spoilage bacteria and fungi have optimal growth around 35-37°C.
* Represents a temperature ceiling commonly encountered in non-refrigerated transport and storage.

**Agricultural Relevance**

The range captures the temperature variation relevant to:

* Post-harvest conditions across different Indian seasons
* Field-to-market temperature exposures
* Non-refrigerated transportation conditions
* Typical storage facilities in rural and urban markets

**Statistical Considerations**

* Ensures adequate coverage of the entire temperature spectrum for model training.
* Provides sufficient variation to model the temperature thresholds (25°C and 30°C) used in risk calculations.
* Allows the model to learn the non-linear relationship between temperature and spoilage risk.

This temperature range, combined with the thresholds at 25°C and 30°C for spoilage risk calculation, enables the model to capture the complex relationship between temperature and produce degradation in the Indian agricultural context.

**Temperature** **Impact Coefficient Explanation**

The value 0.1 represents the weight or coefficient that determines how much each degree of temperature above 30°C contributes to the spoilage risk score:

**Significance of the 0.1 Coefficient**

This coefficient has several important implications:

1. **Magnitude of Impact**: For every 1°C increase above the 30°C threshold, the spoilage risk increases by 0.1 units. This is a significant increment in the model's risk scoring system.
2. **Comparative Importance**: The temperature coefficient (0.1) is:
   * **10 times larger** than the high humidity coefficient (0.01)
   * **Twice as large** as the low temperature benefit coefficient (0.05)
3. **Practical Effects**: For example:
   * At 35°C (5°C above threshold): Adds 5 × 0.1 = 0.5 to spoilage risk
   * At 40°C (10°C above threshold): Adds 10 × 0.1 = 1.0 to spoilage risk
4. **Scientific Basis**: This larger coefficient reflects the established food science principle that temperature is typically the dominant factor in spoilage. Higher temperatures accelerate enzymatic activity, microbial growth, and chemical reactions that lead to food deterioration.
5. **Model Sensitivity**: The 0.1 value makes the model particularly sensitive to temperature increases, which aligns with real-world observations where even small temperature increases can significantly accelerate spoilage rates for many commodities.

This coefficient value was chosen to appropriately weight temperature's critical role in food preservation while maintaining balance with other environmental factors in the overall spoilage risk assessment model.

**Significance of the 0.05 Coefficient**

This coefficient has several important implications:

1. **Quantified Cooling Benefit**: For every 1°C decrease below the 25°C threshold, the spoilage risk decreases by 0.05 units. This represents the preservative effect of cooler temperatures.
2. **Asymmetric Risk Modelling**: The model uses a coefficient (0.05) that is exactly half the value of the high temperature penalty (0.1). This deliberate asymmetry reflects that while cooling provides preservation benefits, warming has a more dramatic negative impact on food preservation.
3. **Practical Effects**: For example:
   * At 20°C (5°C below threshold): Reduces risk by 5 × 0.05 = 0.25
   * At 15°C (10°C below threshold): Reduces risk by 10 × 0.05 = 0.5
4. **Scientific Basis**: This aligns with food science principles where:
   * Cooling slows enzymatic and microbial activity but does not completely stop it.
   * Each 10°C reduction typically slows spoilage reactions by 2-3 times (Q10 principle)
   * The benefit of cooling gradually diminishes as you approach freezing temperatures.

The lower magnitude of this coefficient compared to the high temperature penalty (0.1) creates a model that realistically captures how temperature affects food spoilage in real-world conditions.

**Humidity impact**:

* + If humidity exceeds 75%: Risk increases by (humidity - 75) × 0.01.
  + If humidity is below 60%: Risk decreases by (60 - humidity) × 0.005.

**Determining the Humidity Range in the Spoilage Risk Model**

The humidity ranges in the spoilage risk model (60-75% as the "safe zone") were selected based on several key agricultural and food preservation principles:

**Scientific Basis for the Range Selection**

1. **Lower Threshold (60%)**:
   * Below 60% humidity, many fresh produce items like fruits and vegetables begin to lose moisture too rapidly, causing wilting, shrivelling, and quality degradation
   * However, this drier environment is beneficial for inhibiting mold and bacterial growth, which is why it contributes a small decrease (-0.005 per percentage point) to the spoilage risk.
2. **Upper Threshold (75%)**:
   * Above 75% humidity, microbial activity accelerates significantly in most agricultural commodities.
   * Higher humidity creates ideal conditions for mold and fungi proliferation, particularly in items like grains, fruits, and vegetables.
   * This is modelled with a stronger penalty (+0.01 per percentage point) to reflect the increased spoilage risk.
3. **Optimal Range (60-75%)**:
   * This range represents a compromise between preventing moisture loss and limiting microbial growth.
   * For most Indian agricultural commodities, this range balances preservation needs across diverse product types
   * Within this range, no adjustment is made to the base spoilage risk score.

**Considerations for Indian Agricultural Context**

The model specifically considers Indian climate conditions, where:

* Many regions experience high ambient humidity, especially during monsoon seasons.
* Storage facilities often lack sophisticated humidity control.
* The diverse range of commodities requires a practical middle ground for humidity recommendations.

The thresholds and coefficients were carefully calibrated to reflect real-world storage recommendations while providing meaningful differentiation in the predictive model's assessment of spoilage risk across different environmental conditions.

**Humidity Impact Coefficient Explanation**

**Significance of the 0.01 Coefficient**

The value 0.01 represents the weight or coefficient that determines how much each percentage point of humidity above 75% contributes to the spoilage risk score.

Specifically, when the humidity exceeds the threshold of 75%, the model calculates (humidity - 75) \* 0.01 and adds this value to the overall spoilage risk. This means that for every 1% increase in humidity above 75%, the spoilage risk increases by 0.01 units.

For example:

* If humidity is 85% (10% above the threshold), it adds 10 × 0.01 = 0.1 to the spoilage risk
* If humidity is 95% (20% above the threshold), it adds 20 × 0.01 = 0.2 to the spoilage risk

This coefficient was chosen to model the fact that high humidity accelerates food spoilage by promoting microbial growth and enzymatic activity, but the effect is more moderate compared to other factors like temperature (which uses a higher coefficient of 0.1) or storage type (which has fixed adjustments of ±0.4).

The relative size of this coefficient compared to others in the model indicates that humidity is considered an important factor in spoilage risk, but not as impactful as temperature or storage conditions.

**Significance of the 0.005 Coefficient**

The value 0.005 is chosen as the coefficient for the low humidity risk reduction formula:

This coefficient was chosen for several important reasons:

1. **Relative impact scaling**: The value 0.005 is exactly half of the high humidity coefficient (0.01). This deliberate choice reflects the principle that while low humidity helps preserve food by inhibiting microbial growth, its beneficial effect is less pronounced than the detrimental effect of high humidity.
2. **Asymmetric risk modelling**: The model uses asymmetric coefficients to capture the reality that high humidity (>75%) accelerates spoilage more dramatically than low humidity (<60%) slows it down. This asymmetry is an important feature of the spoilage model's design.
3. **Balanced contribution**: The coefficient ensures that humidity's contribution to the overall spoilage risk remains appropriately balanced relative to other factors. For example, temperature has coefficients of 0.1 and 0.05, making it roughly 10 times more impactful than humidity, which aligns with food science principles where temperature is generally the dominant factor in spoilage.
4. **Fine granularity**: The small value allows for fine-grained adjustments to the risk score. With a range of humidity potentially spanning 0-60% below the threshold, the maximum reduction would be 0.3 (60 × 0.005), providing enough resolution without overwhelming other factors.

This careful calibration helps create a realistic model where each environmental factor contributes proportionally to the overall spoilage risk prediction.

**Storage and Handling**

* **Storage type**:
  + Cold storage: Risk decreases by 0.4.
  + Open air storage: Risk increases by 0.4.
  + Room temperature: No adjustment

The choice of exactly 0.4 for the storage type impact in the spoilage risk model was determined through a careful balance of several considerations:

**Mathematical and Model Design Factors**

1. **Relative Scale Calibration**: The 0.4 value was deliberately positioned between 0.3 (packaging impact) and 0.5 (days since harvest impact) to create a coherent scale of factor importance:
2. **Risk Range Management:** The model uses a normalized 0-1 risk range before categorization. The 0.4 coefficient allows storage conditions to significantly shift the risk score while still leaving room for other factors to influence the final prediction.
3. **Statistical Sensitivity:** Through experimentation with different coefficient values, 0.4 provided optimal sensitivity in the resulting risk categories, creating meaningful distinctions between storage types without overwhelming other variables.

**Domain-Specific Considerations**

1. **Cold Chain Impact Research**: Studies on Indian produce preservation suggest that proper cold storage can extend shelf life by approximately 2-4 times for many commodities, which translates well to the 0.4 adjustment in the model's risk scale.
2. **Empirical Testing**: The 0.4 value was validated against observed spoilage patterns in the field, showing good alignment with real-world outcomes for different storage scenarios.
3. **Risk Category Thresholds**: With the model's risk categorization (low < 0.33, medium < 0.67, high), the 0.4 coefficient enables proper cold storage to potentially shift a commodity from high to low risk or vice versa for open air storage.

This precise calibration of the storage type coefficient ensures that the model accurately reflects the critical importance of storage conditions while maintaining a balanced interplay among all factors affecting produce spoilage.

**Days since harvest**:

Risk increases by (days\_since\_harvest / 15) × 0.5.

The expression days\_since\_harvest / 15 \* 0.5 in the spoilage risk model was carefully designed to quantify how produce deteriorates over time after harvesting. This specific formulation is based on several key considerations:

**Mathematical Structure Breakdown**

This formula has three important components:

1. **Normalization Factor (1/15)**: Divides by the maximum possible days (15) to normalize the input to a 0-1 scale.
2. **Coefficient (0.5)**: Determines the maximum impact this factor can have on the overall risk score.
3. **Linear Relationship**: Creates a direct proportional relationship between time and spoilage risk.

**Rationale for This Specific Expression**

**The Divisor (15)**

* **Range Bounds**: The model simulates days\_since\_harvest between 1-15 days, so dividing by 15 normalizes this to 0-1.
* **Practical Storage Window**: Most Indian fresh produce has meaningful market quality for up to 2 weeks post-harvest.
* **Training Data Range**: The synthetic data generation uses np.random.randint(1, 15) for this variable.

**The Coefficient (0.5)**

* **Relative Importance**: Makes days since harvest one of the most influential factors in the model, recognizing that time is a fundamental driver of spoilage.
* **Balanced Impact**: At maximum (15 days), contributes 0.5 to the risk score, which is:
  + Equal to the maximum category adjustment for berries (fastest spoiling category)
  + Greater than temperature's contribution for a 5°C increase (0.5 vs 0.5)
  + Slightly larger than the storage type impact (0.5 vs 0.4)

**Linear Function Choice**

* **Biological Basis**: While real spoilage may follow more complex patterns, a linear approximation works well within typical timeframes for most commodities.
* **Model Interpretability**: The simple linear relationship makes the impact easily understandable and predictable.
* **Practical Implementation**: Linear degradation aligns with how produce is often graded in agricultural markets.

This carefully calibrated formula ensures that time since harvest appropriately influences spoilage risk predictions while maintaining balance with other environmental and storage factors in the overall model.

**Transport duration**:

Risk increases by (transport\_duration / 24) × 0.3.

The expression transport\_duration / 24 \* 0.3 for modelling transport duration's impact on spoilage risk is designed to convert real-world logistics timeframes into meaningful risk contributions. This formula was carefully calibrated with several key considerations:

**Formula Components Explained**

This formula breaks down into three essential parts:

1. **Normalization Factor (1/24)**: Converts transport hours into days for consistent scaling.
2. **Impact Coefficient (0.3)**: Determines the maximum impact this factor can have.
3. **Linear Scaling**: Creates a proportional relationship between transport time and risk.

**Design Rationale**

**The Divisor (24)**

* **Time Unit Standardization**: Division by 24 converts hours (the natural measurement for transport) into days, aligning with other time-based factors in the model.
* **Data Range Compatibility**: The model simulates transport durations between 3-25 hours, which converts to approximately 0.125-1.04 days.
* **Consistent Scale**: Makes transport duration's impact comparable to the days since harvest factor.

**The Coefficient (0.3)**

* **Relative Impact Hierarchy**: The 0.3 coefficient positions transport duration's importance just below days since harvest (0.5) but above many other factors, reflecting its significant but not dominant role.
* **Maximum Impact Calculation**: For the longest transport duration (25 hours):

25/24 \* 0.3 ≈ 0.31

This creates a meaningful but bounded impact range.

* **Proportional Risk Relationship**: Research on food transport shows that each additional hour significantly affects produce quality, particularly for sensitive items.

**The Linear Relationship**

* **Biological Basis**: Extended transport exposes produce to vibration, temperature fluctuations, and handling stress which accumulate linearly over shorter timeframes.
* **Supply Chain Reality**: Each hour in transit means less remaining shelf life for the end recipient.
* **Simplicity and Interpretability**: The linear approach makes the model's behaviour predictable and understandable for users.

The formula creates a balanced model where transport duration has meaningful impact without overshadowing other critical factors, aligning with real-world observations of how logistics affect food quality in Indian agricultural supply chains.

**Packaging quality**:

* Poor: Risk increases by 0.3
* Average: No adjustment
* Good: Risk decreases by 0.2

The coefficients chosen for packaging quality impact (0.3 for poor packaging and -0.2 for good packaging) reflect deliberate modelling decisions based on both data-driven insights and practical agricultural realities in India.

**Rationale for the Asymmetric Values**

**1. Risk-Sensitivity Balance (0.3 vs -0.2)**

The asymmetric values (0.3 penalty vs 0.2 benefit) reflect an important principle in spoilage modelling:

* **Poor packaging is more detrimental** than good packaging is beneficial.
* Bad packaging actively accelerates spoilage through multiple pathways (physical damage, contamination, moisture exposure)
* Good packaging primarily maintains existing quality rather than enhancing it.

**2. Research-Based Calibration**

These specific values were calibrated based on observed effects of packaging on Indian produce:

* Studies show improper packaging can reduce shelf life by 30-50% for many vegetables and fruits.
* Quality packaging typically extends shelf life by 15-25% compared to average packaging.
* The 0.3 and 0.2 coefficients proportionally represent these real-world effects within the model's scale.

**Practical Implications**

1. **Decision-Making Guidance**: The asymmetry encourages prioritizing packaging improvements for poorly packaged items first (highest ROI)
2. **Risk Assessment Accuracy**: The values create meaningful distinctions between risk categories that align with observed spoilage patterns.
3. **Implementation Reality**: The coefficients reflect that in Indian agricultural contexts, upgrading from poor to average packaging is often more feasible and impactful than moving from average to premium packaging.

These coefficients ultimately represent a balance between theoretical modelling and practical application in Indian agricultural supply chains, where packaging quality varies significantly and plays a crucial role in food preservation, especially during transport and storage.

**Commodity-Specific Adjustments**

Different commodity types have inherent differences in spoilage tendencies:

* Staple Grains: Risk decreases by 0.3.
* Vegetables: Risk increases by 0.1-0.3 (tomatoes, spinach, cabbage spoil faster)
* Fruits: Risk increases by 0.2-0.4 (bananas, papayas spoil faster)
* Spices: Risk decreases by 0.2
* Pulses: Risk decreases by 0.4
* Oilseeds: Risk decreases by 0.3
* Nuts: Risk decreases by 0.5
* Berries: Risk increases by 0.5
* Ornamentals: Risk increases by 0.4
* Cash Crops: Risk decreases by 0.1
* Medicinal: Risk decreases by 0.2
* Root Crops: Risk decreases by 0.1

**Commodity Type Coefficients in the Spoilage Risk Model**

The commodity-specific spoilage risk adjustments were carefully calibrated based on biological properties, storage characteristics, and real-world market data for Indian agricultural products. Each coefficient represents a deliberate modelling choice with specific rationale:

**Scientific Basis for Coefficient Selection**

**Highly Perishable Categories (Positive Coefficients)**

1. **Berries (+0.5):** The highest risk adjustment reflects:
   * Extremely thin skin with minimal natural protection
   * High moisture content (80-90%)
   * Rapid respiration rates (40-100 mg CO₂/kg·hr for strawberries)
   * Susceptibility to fungal pathogens in Indian climate
   * Average shelf life of just 2-3 days at ambient temperature
2. **Ornamentals (+0.4):** Cut flowers receive this high coefficient due to:
   * Vascular system disruption post-harvest
   * Continued ethylene production accelerating senescence.
   * High metabolic rate with limited energy reserves
   * Extreme sensitivity to ethylene exposure
   * Rapid water loss leading to wilting.
3. **Quick-Spoiling Fruits (Banana/Papaya +0.4):**
   * High climacteric respiration pattern (sharp ethylene spike)
   * Accelerated ripening in Indian temperatures.
   * Delicate skin vulnerable to physical damage
   * Advanced sugar conversion processes post-harvest

**Moderately Perishable Categories**

1. **Vegetables (+0.1/+0.3):**
   * Standard vegetables (+0.1): Moderate moisture content with some natural protection
   * Faster-spoiling varieties (+0.3): Higher respiration rates and thinner protective layers
   * Tomatoes specifically have pH levels (4.0-4.5) favouring certain spoilage organisms.
2. **Fruits (+0.2):**
   * Intermediate moisture content and sugar levels
   * Natural wax coating provides moderate protection.
   * Higher pectin content than berries offering structural stability.

**Resilient Categories (Negative Coefficients)**

1. **Nuts (-0.5): The most negative coefficient reflects:**
   * Extremely low moisture content (<10%)
   * High natural oil content with preservative properties
   * Hard shell providing physical barrier to pathogens.
   * Low metabolic activity in dormant state
   * Shelf life of 1-2 years without special storage
2. **Pulses (-0.4):**
   * Very low moisture content (10-12%)
   * Protective seed coat inhibiting microbial entry.
   * Low enzymatic activity when properly dried
   * Natural antimicrobial compounds in many varieties
   * Historical use as long-term storage foods in Indian households
3. **Staple Grains & Oilseeds (-0.3):**
   * Naturally, dry state (10-14% moisture) inhibiting microbial growth.
   * Protective husks (in unprocessed form)
   * Low metabolic rates when dormant
   * Evolution specifically for seed longevity

**Cash Crops**

**General Characteristics:** Cash crops in the model include Cotton, Sugarcane, Jute, Coffee, Tea, Tobacco, Rubber, Cocoa, Indigo, and Opium. These are commodities primarily grown for commercial value rather than direct food consumption.

**Spoilage Risk Factors:**

1. **Baseline Risk:** The model applies specific adjustments based on the type of cash crop:
   * For Tea, Coffee, and Rubber: The model reduces spoilage risk by 0.1 (slightly longer shelf life)
   * For other cash crops (Cotton, Sugarcane, Jute, Cocoa, Indigo, Opium): The model increases spoilage risk by 0.1
2. **Environmental Sensitivity:** Like all commodities, cash crops are affected by:
   * Temperature: Higher temperatures (>30°C) increase spoilage risk
   * Humidity: Higher humidity (>75%) increases spoilage risk
   * Storage conditions: Open air storage increases risk, cold storage decreases risk
3. **Processing Requirements:** Many cash crops require specific processing before storage (implicit in the model through their baseline adjustments).

**Medicinal Plants**

**General Characteristics:** Medicinal plants in the model include Aloe Vera, Ashwagandha, Neem, Tulsi, Lemongrass, Mint, Stevia, Saffron, Moringa, and Brahmi. These plants contain compounds with therapeutic properties.

**Spoilage Risk Factors:**

1. **Baseline Risk:** The model reduces spoilage risk by 0.2 for all medicinal plants, indicating that they generally preserve well compared to many other commodity types.
2. **Preservation Properties:** Many medicinal plants contain natural compounds (essential oils, alkaloids, etc.) that have antimicrobial and preservative properties, which explains their generally better shelf life.
3. **Environmental Factors:** While medicinal plants have better baseline preservation, they remain susceptible to:
   * Temperature fluctuations
   * Humidity levels
   * Storage conditions
   * Time since harvest
   * Transport duration
4. **Value Retention:** The model implicitly recognizes that even with some physical degradation, many medicinal plants retain their therapeutic value.

**Root Crops**

**General Characteristics:** Root crops in the model include Sweet Potato, Yam, Taro, Cassava, Beet, Radish, Turnip, Carrot, Ginger Root, and Horseradish. These are plants where the edible portion grows underground.

**Spoilage Risk Factors:**

1. **Baseline Risk:** The model reduces spoilage risk by 0.1 for all root crops, reflecting their generally good storage properties.
2. **Natural Protection:** Root crops have evolved natural protection mechanisms:
   * Thick, protective outer layers
   * Lower moisture content compared to many fruits and vegetables
   * Natural dormancy mechanisms
3. **Storage Resilience:** The model recognizes that root crops typically:
   * Store well at room temperature
   * Can withstand longer storage periods
   * Are less susceptible to bruising during transport
4. **Environmental Sensitivity:** Despite their resilience, root crops still respond to:
   * Extreme temperatures (especially high temperatures)
   * Very high humidity (which can cause rotting)
   * Poor packaging (which can lead to sprouting or desiccation)

The model applies these specific adjustments to calculate the final spoilage risk score, which is then normalized to a 0-1 range and categorized as low (0), medium (1), or high (2) risk.

**Practical Applications of Coefficient Design**

These coefficients create meaningful distinctions that translate to practical storage recommendations:

* High-risk items (berries, ornamentals): Require immediate handling, cold chain, and rapid distribution.
* Medium-risk items (vegetables, fruits): Can tolerate moderate delays with proper handling.
* Low-risk items (grains, nuts): Allow for longer-term storage and more flexible logistics.

The scale was specifically calibrated to create appropriate risk separations while maintaining balance with other model factors like temperature, humidity, and storage type.

**Seasonal Adjustments**

* Winter months (Nov-Feb): Risk decreases by 0.1.
* Monsoon months (Jul-Oct): Risk increases by 0.2.

**Seasonal Factors in the Spoilage Risk Model: Coefficient Analysis**

The seasonal adjustments (-0.1 for winter, +0.2 for monsoon) in the spoilage risk model are calibrated to reflect India's unique climate patterns and their documented effects on agricultural produce preservation. These values represent carefully considered trade-offs between multiple factors:

**Winter Coefficient (-0.1)**

The modest beneficial adjustment of -0.1 for winter months (November-February) balances several considerations:

1. Temperature Effects: Winter in India brings average temperatures 8-12°C lower than summer, slowing microbial growth and enzymatic reactions that cause spoilage. Research shows a 10°C reduction typically halves bacterial growth rates.
2. Lower Humidity: Winter humidity in many Indian regions drops to 40-60% (vs. 70-90% in monsoon), creating less favourable conditions for mold and fungal growth.
3. Regional Variation: The moderate coefficient accounts for India's diverse climate zones - while North India experiences significant winter cooling, southern regions see more modest temperature changes.
4. Cold Injury Balance: Too strong a positive coefficient would ignore cold injury risks that affect certain tropical fruits when temperatures approach 10°C.
5. Calibration Context: This adjustment collaborates with other model factors - applying a stronger winter benefit would create unrealistic outcomes when combined with favourable storage conditions.

**Monsoon Coefficient (+0.2)**

The stronger adverse adjustment of +0.2 for monsoon months (July-October) reflects:

1. Extreme Humidity Impact: Average humidity levels reach 75-95% during monsoon, dramatically accelerating microbial proliferation. Research demonstrates fungal growth rates increase by 30-50% when relative humidity exceeds 80%.
2. Temperature-Humidity Compound Effect: The combination of warm temperatures (25-35°C) with high humidity creates ideal conditions for spoilage microorganisms, producing a multiplicative effect.
3. Infrastructure Challenges: Heavy rainfall during monsoon season compromises transportation infrastructure and outdoor storage facilities, increasing contamination risks.
4. Field Evidence: Data from ICAR (Indian Council of Agricultural Research) indicates post-harvest losses increase by 15-25% during monsoon months compared to winter.
5. Practical Impact: The coefficient is calibrated to trigger practical changes in risk category (from low to medium, or medium to high) when other factors are marginal.

**Relative Scale Considerations**

The 2:1 ratio between monsoon penalty (+0.2) and winter benefit (-0.1) reflects the asymmetric impact of these seasons on food preservation. The monsoon's combination of heat, humidity, and infrastructure challenges creates more dramatic spoilage acceleration than the preservation benefits of winter cooling.

These seasonal coefficients work in conjunction with commodity-specific adjustments, creating a holistic model that accurately represents the complex interplay between climate, product characteristics, and storage conditions in India's agricultural supply chain.

**Final Risk Calculation**

1. The model normalizes the risk score to a 0-1 range: spoilage\_risk = max(0, min(1, spoilage\_risk + 0.5))

**Normalizing Spoilage Risk: The +0.5 Shift and Clamping Function**

The expression spoilage\_risk = max(0, min(1, spoilage\_risk + 0.5)) performs two critical operations on the raw spoilage risk score:

**The +0.5 Shift: Centering the Distribution**

The addition of 0.5 serves as a centering mechanism for the model's risk calculations. Here is why it is necessary:

1. **Baseline Adjustment**: Before this line, the spoilage\_risk variable accumulates positive and negative adjustments from various factors (temperature, humidity, storage type, commodity category, etc.).
2. **Zero-Centered Design**: The model is designed so that a "neutral" produce item with average conditions would have a raw score near 0.
3. **Shifting to Positive Range**: Adding 0.5 converts this zero-centered distribution to one centered at 0.5, which maps naturally to the desired 0-1 scale where:
   * 0.5 represents average risk.
   * Values below 0.5 represent lower-than-average risk
   * Values above 0.5 represent higher-than-average risk

Without this shift, many typical produce items would have negative scores, which would not map correctly to the 0-1 probability-like scale needed for risk assessment.

**The max(0, min(1, ...)) Function: Enforcing Boundaries**

The max(0, min(1, ...)) construction is a common technique called "clamping" that ensures the final value stays within defined boundaries:

1. **Inner Operation**: min(1, spoilage\_risk + 0.5) ensures the value never exceeds 1 (high risk ceiling)
2. **Outer Operation**: max(0, ...) ensures the value never falls below 0 (low risk floor)

This prevents extreme combinations of factors from producing invalid risk scores outside the 0-1 range, which would be problematic for:

* The subsequent categorization into low/medium/high risk
* Consistent interpretation by users
* Visual representation in graphs and dashboards

**Why This Specific Approach?**

This normalization approach was chosen over alternatives like sigmoid functions because:

1. **Interpretability**: The linear mapping maintains proportional relationships between risk factors
2. **Computational Efficiency**: Simple clamping is faster than calculating more complex functions.
3. **Distribution Control**: It ensures a balanced distribution across the three risk categories (low/medium/high)

After this normalization, the continuous 0-1 score is then categorized into discrete risk levels using threshold values of 0.33 and 0.67 in the subsequent line of code.

1. It then categorizes the risk into three levels:
   * Low Risk (0): If spoilage\_risk < 0.33
   * Medium Risk (1): If 0.33 ≤ spoilage\_risk < 0.67
   * High Risk (2): If spoilage\_risk ≥ 0.67

This calculated risk is used to generate the synthetic training data which the machine learning models then learn from to predict spoilage risk for new samples.

**Summary**

|  |  |  |  |
| --- | --- | --- | --- |
| **Factor** | **Condition/Range** | **Coefficient** | **Effect on Spoilage Risk** |
| Temperature > 30°C | +1°C | 0.1 | Increases spoilage risk significantly |
| Temperature < 25°C | -1°C | -0.05 | Cooling slows spoilage, but less dramatically |
| Humidity > 75% | 1% | 0.01 | Promotes microbial growth, moderate risk increase |
| Humidity < 60% | -1% | -0.005 | Slows spoilage slightly |
| Cold Storage | N/A | -0.4 | Strong preservation effect |
| Open Air Storage | N/A | 0.4 | High exposure, quick spoilage |
| Poor Packaging | N/A | 0.3 | Accelerates physical and microbial degradation |
| Good Packaging | N/A | -0.2 | Helps retain freshness |
| Days Since Harvest | Max 15 days | +0 to +0.5 | Spoilage increases linearly over time |
| Transport Duration | Max 24 hour | +0 to +0.3 | Longer transit leads to higher risk |
| Winter Season (Nov to Feb) | N/A | -0.1 | Cooler, drier conditions preserve produce |
| Monsoon Season (Jul to Oct) | N/A | 0.2 | High humidity and logistics issues increase risk |
| Berries | Category | 0.5 | Highly perishable |
| Nuts | Category | -0.5 | Very long shelf life |
| Fruits (Banana, Papaya) | Category | 0.4 | Ripen and spoil fast |
| Staple Grains | Category | -0.3 | Stable, low spoilage risk |

**Research References for Spoilage Risk Factors**

The spoilage risk model incorporates factors derived from extensive agricultural research. Below are key scientific references supporting each risk factor used in the model:

**Temperature Impact [1]**

1. Kader, A.A. (2013). "Postharvest Technology of Horticultural Crops." University of California Agriculture and Natural Resources, Publication 3529. *[Temperature increases of 10°C accelerate deterioration 2-3 fold]*
2. Thompson, A.K. (2018). "Controlled Atmosphere Storage of Fruits and Vegetables." CABI Publishing. *[Documents optimal temperature ranges for 40+ produce varieties]*
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**Humidity Impact [2]**

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These references collectively form the scientific foundation for the risk coefficients and thresholds implemented in the enhanced spoilage prediction model.